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From prairie to crop: Spatiotemporal dynamics of surface soil organic carbon stocks over 167 years in Illinois, U.S.A.

Nan Li [a], Shengnan Zhou [a], Andrew J. Margenot [a,b,*]

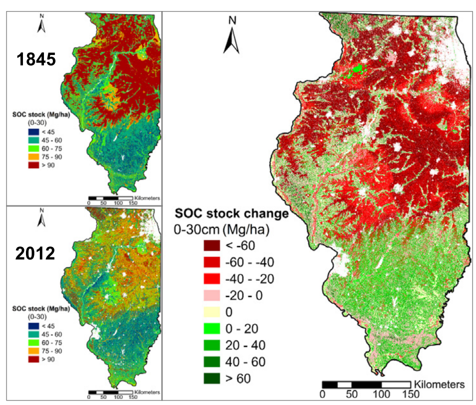
[a] Department of Crop Sciences, University of Illinois Urbana-Champaign, Urbana, IL 61801, USA
[b] Agroecosystem Sustainability Center, Institute for Sustainability, Energy, and Environment, University of Illinois Urbana-Champaign, Urbana, IL 61801, USA

HIGHLIGHTS

- Space-for-time substitution used to predict 167 year SOC stocks change in Illinois
- Supplementing legacy data with native land use observations improves backcasting.
- Land use change impacts on SOC stocks differed by soil type.
- Conversion from prairie and forest to cropland result up to 50 % SOC stock loss
- Greatest decreases in SOC stock occurred for Endoaquolls under prairie.

GRAPHICAL ABSTRACT

Soil organic carbon (SOC) over 167 years of land use change



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ABSTRACT

Quantifying spatiotemporal dynamics of soil organic carbon (SOC) stocks is needed to understand the impact of land use change and can help target carbon sequestration efforts. In the recently and radically transformed landscapes of the state of Illinois, U.S.A., we evaluated surface SOC stocks under land use change using a space-for-time substitution method over 167 years. Additionally, we determined SOC stocks for the A horizon vs 0–30 cm depth to evaluate pedogenically-informed vs more commonly used fixed depth approaches. Legacy soil datasets from 1980 to 2012 were combined with environmental covariates using a random forest algorithm. To more accurately estimate pre-agricultural land use SOC stocks (i.e., pre-1845), SOC observations collected from soils under native prairie and forest were extracted from peer-reviewed publications. The model was validated on 25 % of the total 627 test data ($R^2_{A\text{-hor}}$: 0.59 and $R^2_{0\text{–}30}$: 0.56; $RMSE_{A\text{-hor}}$: 20.5 and $RMSE_{0\text{–}30}$:19.3 Mg/ha) independent of the 75 % of data for calibration (R^2: 0.91; $RMSE_{A\text{-hor}}$:10.1 and $RMSE_{0\text{–}30}$:9.6 Mg/ha). SOC stocks were largest under prairie (A horizon: 156.1 Mg/ha; 0–30 cm: 152.4 Mg/ha) and lowest under pasture (A horizon: 33.2, 0–30 cm: 44.6 Mg/ha). SOC stocks varied less by soil order than by land use. Between 1845 and 2012, surface SOC stocks decreased for most of Illinois, with greatest losses in central (−16.3 Mg/ha) and east-central Illinois (−47.0 Mg/ha) where approximately 80 % of prairie was converted to cropland. A slight increase in surface SOC stocks occurred in the unglaciated northwest region and the less recently glaciated south region, as well as in alluvial corridors. This study (i) highlights how estimating spatiotemporal dynamics of surface SOC stocks over centennial timescales can benefit from including measures of SOC under native land use not usually contained in legacy pedon datasets, and (ii) illustrates the potential of identifying localized hotspots of historical SOC loss and thus deficits that can be prioritized for carbon sequestration efforts.

Abbreviations: SOC, soil organic carbon.

* Corresponding author at: Department of Crop Sciences, University of Illinois Urbana-Champaign, Urbana, IL 61801, USA.
E-mail address: margenot@illinois.ed (A.J. Margenot).

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1. Introduction

Soils serve as the largest terrestrial sink of carbon, accounting for an estimated 75 % of global terrestrial pool, and are therefore critical to help mitigate climate forcing (Johnston et al., 2004). Land use change from native ecosystems to agricultural land use typically incurs net soil organic carbon (SOC) losses (Scharlemann et al., 2014) and is the second-largest source of historical greenhouse gas emissions (20–25 % of total). Significant declines in SOC stocks have been documented following the conversion of forests and grasslands to agricultural land use (Lal, 2004; Laganière et al., 2010). Globally, Buringh (1984) estimated an average SOC loss (to 100 cm depth) of 48 % for the conversion of forest to cropland, 28 % for the conversion of forest to grassland, and 35 % for the conversion of forest to cropland or pasture. Agricultural conversion of grasslands such as prairies, a globally important biome, generally entails a 50 % to 70 % loss in SOC (Lal et al., 2007). For example, in central Illinois, reductions in SOC of Mollisols with annual crop cultivation ranged 21–52 % at 0–20 cm depth relative to native prairie (David et al., 2009). Within only the past two centuries, prairies in North America have been transitioned to agricultural land use, implying deep historical SOC deficits.

The North Central United States is today a region of intensive and highly productive agriculture, but its transformation from prairie and forest occurred in less than two centuries, enabling the possibility of using legacy soil data and remnant native vegetation sites to estimate changes in SOC stocks with agricultural conversion. In contrast, other major temperate grassland and forest biomes have accrued agriculturally-induced SOC deficits over multiple centuries or even millennia (e.g., East Asia, southern Europe) (Sanderman et al., 2017). Situated in the heart of this highly productive region often referred to by the eponymous name of the Corn Belt, Illinois represents drastic changes in land use and land cover (LULC). Such changes are broadly understood but specifically unresolved with respect to alteration of SOC stocks, initiated with European-American invasion and settlement in the mid-1800s. Over the subsequent sesquicentennial period, large-scale conversion of native tallgrass prairies and deciduous forest to agricultural production had led to >75 % of the total land area of Illinois today being devoted to annual crop production; only 19 % of native forests (Iverson, 1988) and 0.01 % of the native prairie remain (White and Corbin, 1978). Though previous studies have assessed localized LULC impacts on SOC change in Illinois, these are limited to the watershed or field scale (e.g., Yadav and Malanson, 2008; Yu et al., 2018; Olson and Gennadiev, 2020). Additionally, observations of native vegetation extent pre-1900s and of SOC stocks under native vegetation steady-state are limited in availability and often low spatial resolution, constraining the accuracy of regional estimates of historical SOC stock changes.

Estimating SOC stock under different land uses and land-management activities can be challenged by the lack of long-term soil archives, mandating the use of space-for-time assessments (Pickett, 1989). However, a challenge to space-for-time assessments for SOC dynamics with land use change is the recency of land use change and/or sufficient records of pre-agricultural conversion SOC stocks. Since legacy pedon data in agriculturally dominant regions like Illinois were collected well after the initiation of agriculture, observations of SOC under original land use are highly limited in number and spatial coverage, hindering estimates of SOC changes over large regions (e.g., state-scale). Techniques for estimating SOC stocks can be divided into two general methods of spatial extrapolation, including the measure-and-multiply approach and soil-landscape modelling approaches (Cambule et al., 2014). In the measure-and-multiply approach, environment covariates are used to stratify larger areas into different strata, and point measurements of SOC within each of these strata are averaged and multiplied by the aerial extent of that stratum (Thompson and Kolka, 2005). In the U.S.A., average SOC values from the State Soil Geographic (STATSGO) and the Soil Survey Geographic (SSURGO) databases can be used to estimate SOC stocks across spatial scales (Guo et al., 2006).

However, this approach can have high estimation errors because it does not represent soil and environmental variable heterogeneity within each stratum (Mishra et al., 2010). Alternatively, digital soil mapping offers a means to fulfil the need for accurate soil information at different spatial resolutions and extents (Yigini and Panagos, 2016). A number of DSM techniques using soil-landscape models have been used to estimate the spatial variability of SOC stocks with respect to variations in environmental covariates such as topography, climate, land use, vegetation, parent material, and soil type (Were et al., 2016). A model built based on the various environmental covariates covering the entire study area plus a limited number of field observations can then be used to make predictions of soil properties over a grid across the study area (Huang et al., 2019; Adhikari and Hartemink, 2015).

We applied state-of-the-art digital soil mapping techniques to predict and map SOC stock changes over 167 years in Illinois, from dominantly prairie and forest at the initiation of European-American settlement in the mid-1800s to dominantly annual crop production today. Spatial relationships among measured SOC stocks and the environmental covariates were established using random forest, and SOC stocks were estimated and mapped. The space-for-time substitution method was used to backward predict SOC stocks in 1845 through the use of time-varying LULC recorded at historical past timepoints. We evaluated SOC stocks in surface soils as both A horizon and the surface 0–30 cm layer because pedon-scale SOC stocks are commonly driven by A horizon thickness (Grüneberg et al., 2010), and the A horizon designates a genetic layer developed by pedogenic processes directly relevant to SOC accrual and loss. In contrast, the majority of SOC studies and inventories use a fixed depth of 0–30 cm (e.g., IPCC, 2003; Adhikari et al., 2019; Huang et al., 2019). In addition, surface SOC stocks have been found to be more sensitive than subsurface SOC stocks to land use change (Wang et al., 2004). Therefore, the objectives of this paper were to (i) provide a baseline surface SOC stock map for the A horizon and top 0–30 cm depths in Illinois, (ii) predict surface SOC stocks in 1845 using the space-for-time substitution method, and (iii) quantify spatially explicit historical changes in surface SOC stocks and their relationship to LULC.

2. Material and method

2.1. Study area

Illinois is located in the North Central U.S.A. (36°58′ N to 42°30′ N, 87°30′ W to 91°31′ W) with an area of 149,997 km^2. The state has a lower mean elevation (180 m) than the surrounding states, with the elevation ranging from 85 m at the southernmost tip to 376 m above sea level in the northwest. Landforms and soils vary across the state largely as a result of recent glaciation (Corbett and Anderson, 2006b). Areas that did not undergo glaciation in the Quaternary in the northwest (i.e., Driftless region) and the southern region that less recently underwent glaciation (Illinoian episode) have moderate to highly dissected topography, whereas most of the recently glaciated area (Wisconsinan episode) is relatively flat with slopes <1 % (Fehrenbacher et al., 1967; Willman and Frye, 1970). Glaciation also affected drainage patterns within the state and deposited parent material, notably glacial till and outwash deposits (Risser et al., 1981).

Soils developed primarily from loess occupy about 63 % of the state's land area, predominating in the western, central, and southern regions. Other soils, particularly in the northwestern, west-central, and east-central portions of the state, formed from Pleistocene sand deposits (Fehrenbacher et al., 1967). Five of the 12 soil orders of the United States Department of Agriculture (USDA) Soil Taxonomy are identified in Illinois: Alfisols, Mollisols, Entisols, Inceptisols, and Histosols. Alfisols and Mollisols are the most extensive, accounting for 45 % and 43 % of the state's land area, respectively (Fig. 1).

The majority of Illinois has a humid continental climate (Dfa, Köppen climate classification) with hot, humid summers and cool to cold winters. The southernmost quarter of the state borders on a humid subtropical climate (Cfa, Köppen climate classification) with moderate winters. Annual mean precipitation for Illinois increases from 890 mm in the north to 1200 mm at the southernmost extent. Mean annual temperature ranges from 4.0 (north) to 9.4 °C (south). The land cover consists of (1) cultivated

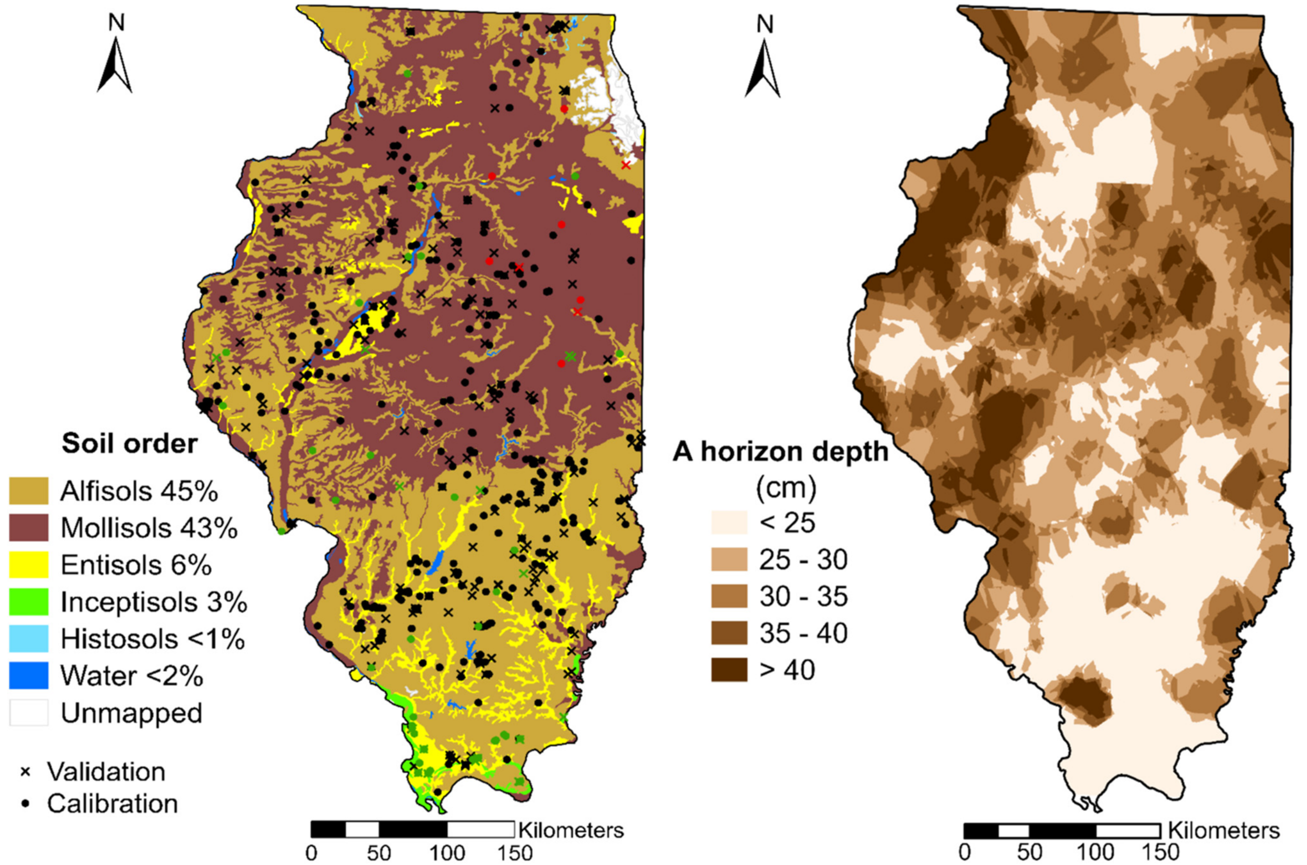

Fig. 1. (Left) Locations of calibration and validation soil profiles overlain on soil map (order level) across Illinois, USA. Red dots represent soils under native remnant prairie and green dots represent soils under native remnant forest; (Right) A horizon depth (cm).

crops of maize (*Zea mays* L.; 51 % of cultivated acreage), soybean (*Glycine max* L.; 46 %) with minor amounts of wheat (*Triticum aestivum* L.; 3 %) (USDA, 2020); (2) pasture, defined as areas of grasses, legumes, or grass-legume mixtures planted for livestock grazing; (3) forest (deciduous, evergreen and mixed); (4) prairies; and (5) wetland vegetation. Native vegetation pre-agricultural conversion often co-varies with soil type at the USDA taxonomic level of Order: Alfisols generally supported forest, Mollisols supported prairies, and Histosols were formed from the remains of plants in low-lying areas (wetland).

2.2. Soil carbon data

Soil organic carbon concentrations and bulk density values used to calculate surface SOC stocks were obtained from the National Cooperative Soil Survey (NCSS) characterization database (Soil Survey Staff, 2022). To better estimate Illinois SOC stocks in 1845 under native prairie and forest ecosystems, SOC stocks under native (remnant) prairie and forest that had never been cultivated were extracted from the peer-reviewed literature (David et al., 2009; Willand and Baer, 2019; Chen and D'Arcy, 2016; Hansen and Gibson, 2014; Olson et al., 2012, 2011; Olson, 2007; Allison and Jastrow, 2006; Ampleman et al., 2014). This provides observations of surface SOC stocks under native vegetation not captured by legacy data, which was collected in the second half of the 20th century after the majority of agricultural conversion had occurred. In total, SOC concentrations for 627 locations across Illinois were collected from 1980 to 2012 (Fig. 1). For each horizon, SOC was determined by the Walkley–Black method. The horizon specific SOC was then harmonized using an equal-area spline (Bishop et al., 1999) function to generate the SOC for the topsoil (0–30 cm). The 0–30 cm depth was chosen because it is most sensitive to changes in land use conversion (Wang et al., 2004) and because it is commonly used as a fixed depth in many international SOC stock assessments (e.g. FAO, 2019).

The SOC stock was calculated using the following equation:

$$SOC\ stock_{\mathrm{tons/ha}} = \frac{SOC_{\mathrm{g/kg}} \times BD_{\mathrm{g/cm^3}} \times D_{\mathrm{cm}}}{10}$$

where, SOC stock in Mg/ha, SOC soil organic carbon content (g/kg), BD bulk density (g/cm^3), and D is the soil thickness (cm). In this study, measured bulk density values were used for 622 out of the total of 627 soil samples. For the remaining 5 soil samples, SOC stock was reported, but not bulk density. The data set was randomly divided into calibration datasets (consisting of 75 % data) and validation datasets (25 % data) for further analysis.

2.3. Environment covariate

Environmental covariates including terrain attributes, LULC and soil order classification were used to develop the prediction model (Table 1). Terrain attributes were extracted from a digital elevation model (DEM) at 30 m resolution downloaded from the United States Department of Agriculture (USDA) GeoSpatialDataGateway. Eight terrain attributes were extracted using ArcGIS (Conrad et al., 2015), including slope, aspect, hill shade, topographic wetness index (TWI), Stream Power Index (SPI), flow direction, curvature, and elevation.

Yearly LULC projections were obtained from the US Geological Survey (USGS) Modeled Historical Land Use and Land Cover for the Conterminous United States at 250 m resolution (Sohl et al., 2016) with 16 LULC classes. The projected LULC was generated using Landsat imagery in combination with the data from the Agriculture Census, Population Census, USGS Land Cover Trends, and other sources. The LULC classes were regrouped into 5 major LULC classes including cropland, grassland, forest, pasture and wetland to test LULC impacts on the SOC stocks over time. Data on soil order

Table 1
Summary of environmental covariates for developing the random forest model used to estimate surface soil organic carbon (SOC) stocks in Illinois.

Covariates	Description	Source
Elevation	Elevation of the land surface	Derived from the DEM
Slope (°)	Local slope gradient in degree	Derived from the DEM
Topographic wetness index (TWI)	Frequencies and duration of saturated conditions	Derived from the DEM
Aspect	The direction of the steepest slope from the North (degree)	Derived from the DEM
Stream Power Index (SPI)	The erosive power of the terrain	Derived from the DEM
Hill shade		Derived from the DEM
Flow accumulation	Upslope number of grid cells	Derived from the DEM
Curvature	Curvature of the surface itself	Derived from the DEM
LULC	Land cover data adopted in Illinois (5 classes)	US Geological Survey (USGS) Modeled Historical Land Use and Land Cover at 250 m
Soil order	USDA Taxonomy soil order (4 classes)	Derived from gSSURGO

classification were extracted from the USDA Natural Resources Conservation Service (NCRS) Soil Survey geographic database (SSURGO) soil order maps (Soil Survey Staff, 2022).

2.4. Soil organic carbon stock prediction and mapping

Spatial estimations of the SOC stock at A-horizon and 0–30 cm layer were performed from the legacy measured soil profiles using the environment covariates described above. The soil values retrieved from the measured profiles were first joined to the environment covariates using either nearest neighbour or point-in-polygon procedures. First, Random Forests (RF) was implemented to construct the relations between SOC stocks and environment covariates for both A-horizon and 0–30 cm layers. A machine learning approach, RF consists of an ensemble of randomized classification and regression trees model (Breiman, 2001) that generate a tree structure by partitioning the data of a learning sample recursively into a number of groups, where each division is chosen to maximize some measure of difference among the response variables in the resulting two groups. RF combines many trees that are obtained randomly from training samples and independently sampled values (out-of-bag data with the same distribution for all trees in the forest). The RF analysis was performed using the R package Random Forest (Liaw and Wiener, 2002). The selected RF parameters were as follows: ntree (the number of trees in the forest) = 1000, and ntry (number of variables tried at each split) = 5. The model also quantifies the relative importance (RI %) of a predicting covariate based on its usage in prediction. The model fitting was performed in R software using the *randomForest* package along with the train function from the *caret* package (Liaw and Wiener, 2002) to fit the model using the calibration dataset.

Spatial patterns of residuals, calculated as the difference between measured and RF predicted surface SOC stocks at each location, were kriged to capture the spatial variability not modelled by RF. The residuals were then estimated using ordinary kriging and either Spherical, Gaussian or Exponential variogram were fitted (R package Gstat; Pebesma and Graeler (2015)). Once constructed, prediction RF models were applied to the full set of environmental covariates to predict SOC stock at a 250 × 250 m grid. The kriged residuals were then added to the RF predicted values to obtain the final estimates of surface SOC stocks. This two-step mapping approach is referred to as regression kriging (RK; Odeh et al. (1995)) and enables the incorporation of spatial autocorrelation of the residuals in the prediction.

2.5. Backward prediction to 1845 and 1938

Based on the calibrated RF model, the SOC stock of A horizon and 0–30 cm layer was predicted for 1845 and 1938 by changing the environmental covariates (terrain attributes, soil suborder, LULC), equivalent to a space-for-time substitution approach (Pickett, 1989; Adhikari et al., 2019) in which contemporary spatial phenomena are used to model temporal processes that are not directly observable (e.g., historical SOC stocks). The method assumes that the relationship between measured soil properties and spatially varying environmental driving factors modelled at a given timepoint can be extrapolated to other timepoints by substituting the environmental factors at that time to predict the spatial variations of soil properties (Adhikari et al., 2019; Huang et al., 2019). In other words, drivers of SOC stock distributions such as LULC in a given area are assumed to explain temporal changes in SOC stocks. In our case, topography and parent material can be assumed to be stable over the 167 year period.

The year 1845 was selected to investigate the LULC induced surface SOC stock changes because this period pre-empts the dramatic changes in the landscape of Illinois and in general the greater North-Central U.S.A. that soon followed in the late 1800s (Iverson, 1988). Additionally, limited land cover data from state surveys are available pre-1900 but exist for 1845. The SOC stock in 1845 was considered a baseline for investigating the effects of agricultural conversion and subsequent (post-mid-20th century) agricultural intensification (e.g., mechanization, synthetic fertilizer use) on surface SOC stocks, because agricultural land use at this time was <0.2 % based on the landcover survey of Illinois in the early 1800s.

3. Results

3.1. Descriptive statistics of SOC stocks

Measured SOC stocks for the A horizon vs the 0–30 cm depth layer varied by soil-landscape combinations from 1980 to 2012 (Table 2). Prairie occupied the smallest number of sampled sites (0.6 %) but had the largest SOC stock on a per-area basis (156.1 Mg/ha) in A horizons. The second-largest SOC stock in A horizons was found under forest (60.3 Mg/ha), which occupied the largest number of sampled sites (54.6 %). Pasture occupied the second largest number of sample sites (20.7 %) but had the lowest SOC stock (39.8 Mg/ha) in A horizons. Under cropland, Mollisols had the largest SOC stock (75.8 Mg/ha), whereas Alfisols (41.6 Mg/ha) and Entisols (41.0 Mg/ha) had similar SOC stocks. Under pasture and forest, Mollisols also had the largest SOC stock (59.0 and 78.1 Mg/ha, respectively).

Surface SOC stocks on the basis of the fixed 0–30 cm depth showed similarities but also differences with stocks on an A horizon basis. SOC stocks at 0–30 cm depth were greatest for prairie (147.4 Mg/ha), followed by forest (76.1 Mg/ha), wetland (72.1 Mg/ha), cropland (59.5 Mg/ha) and pasture

Table 2
Soil organic carbon (SOC) stock (Mg/ha) under different soil types (USDA order) and land use and land covers (LULC) combinations for the period of 1980–2012.

	Cropland		Forest		Pasture		Prairie		Wetland	
	A horizon	0–30 cm	A horizon	0–30 cm	A horizon	0–30 cm	A horizon	0–30 cm	A horizon	0–30 cm
Alfisols	41.6	46.8	50.8[a]	70.7[b]	37.5[a]	46.1[b]			24.1	27.5
Entisols	41.0	44.1	60.1[a]	85.8[b]	35.5	40.8			60.3[a]	101.1[b]
Inceptisols			52.5	75.4					56.0	40.4
Mollisols	75.8	70.4	78.1	106.9	59.0	61.6	156.1	147.4	57.7	58.2
Average	60.3	59.5	54.3[a]	76.1[b]	39.8[a]	47.3[b]	156.1	147.4	56.4	72.1
CV	64.9	45.5	61.5	46.8	56.3	46.3	21.0	13.4	42.2	45.5

Means followed by the different letters are statistically different at $p < 0.05$.

(47.3 Mg/ha). Under wetland, Entisols had the largest surface SOC stock (101.1 Mg/ha), but for cropland, forest and pasture land use, Mollisols had the largest surface SOC stock. On a fixed depth basis, SOC stocks were lower than for A horizons under the prairie, which reflected a thicker A horizon under prairie that was on average 5.7 cm deeper than for the fixed 0–30 cm sampling depth. Except for prairie, SOC stock for the 0–30 ?thyc = 5? > cm layer under cropland, forest, pasture and wetland were greater than for A horizon stocks.

3.2. Land use/land cover changes from 1845 to 2012

Drastic state-wide LULC changes between 1845 and 2012 remained relatively stable after 1938 (Fig. 2). In 1845, about 54.1 % and 41.7 % of Illinois, approximately 21 and 16 million acres, once were prairie and forest, respectively (Fig. 3a). Prairies were mainly in the northern two-thirds of the state with forests in the southern third. By 1938, prairie had decreased to 0.5 % of the state as the result of the conversion to pasture or cropland, whereas forested area decreased to 14.0 % (Fig. 3b). Concurrently in 2012 (Fig. 3d), the area of cropland increased to 53.5 % and the area of pasture increased by 24.9 %. Land cover was relatively constant from 1938 to 2012, with <5 % changes in land use types. The prairie extent used in our study is slightly different from the 0.01 % of land area under prairie reported by Iverson (1988), likely due to previous maps of prairies in Illinois excluding many of the smaller prairies.

3.3. Importance of predictor variables and RF model performance

The relative importance of environment covariates for SOC stock prediction was identified by the relative usage of covariates in the RF model. Elevation was the most important environment covariate in explaining the spatial distributions of SOC stock for both the A horizon and 0–30 cm layer (Fig. 4). For A horizon stocks, less important but still of major dominance was soil order, whereas the LULC was the third most important variable impacting the spatial pattern of SOC stocks. In contrast, for 0–30 cm stocks, LULC and soil order were the second and third most important. In both cases, flow direction was the least important variable to model the spatial pattern of SOC stocks. The importance of the remaining six topographic covariates differed slightly between A horizon and 0–30 cm layer SOC stocks.

The performances of RF models for predicting SOC stocks of the A horizon and 0–30 cm layer were indicated by Lin's concordance, R^2 and RMSE. RF models had high accuracy for the calibration data (75 %) and performed moderately well based on the validation (25 %) data sets (Fig. 5). For example, RF performance was better for calibration data, with a higher Lin's concordance (0.93) and R^2 (0.91) and smaller RMSE (10.07) compared to validation data (0.72, 0.59 and 20.50, respectively). Similarly, for the 0–30 cm layer, the RF model had a higher Lin's concordance (0.94) and R^2 (0.91) and smaller RMSE (9.57) in calibration data and compared to validation data (0.73, 0.56 and 19.32, respectively).

3.4. Spatial distribution of SOC stock

The RF modelling produced prediction maps of SOC stocks for A horizon (Fig. 6). In general, SOC stocks of A horizons varied significantly across the state. Generally, A horizon SOC stocks decreased from the north and central region to the southern region of the state. This spatial SOC trend was similar from 1845 to 2012 and reflects the distribution patterns of soil order and LULC. Highest predicted A horizon SOC stocks (>90 Mg/ha) occurred in the central and east-central regions as well as the west-central forest-prairie region, largely on Mollisols. The lowest predicted SOC stocks of A horizon (<45 Mg/ha) were located in the south-central forest area, dominated by Alfisols. In the western and west-central Illinois, which encompasses the wetland and floodplains of the Illinois and Mississippi rivers, surface SOC stocks were comparatively moderate (60–70 Mg/ha). In the bottomlands and the loess-covered uplands bordering the Wabash River and its major tributaries in southeastern Illinois, mapped largely as Entisols, SOC stocks were moderate to low (45–60 Mg/ha). SOC stocks in the 0–30 cm layer were similarly distributed as for A horizon stocks (Fig. 7). The major difference in predicted SOC stocks by A horizons versus 0–30 cm depth occurred in the central and east-central region formerly occupied by the Grand Prairie, where A horizon (>90 Mg/ha) shows relatively larger SOC stocks than 0–30 cm layers (75–90 Mg/ha). In the south-central forest area, A horizon (<45 Mg/ha) shows relatively smaller SOC stocks than 0–30 cm layers (45–75 Mg/ha).

3.5. Changes in SOC stock over 167 years

Changes in SOC stock between 1845 and 2012 SOC varied by location and generally entailed net losses over time regardless of whether stocks were calculated on the basis of the A horizon or 0–30 cm depth layer (Fig. 8). Greatest SOC stock losses occurred during the transition of native vegetation to cropland. The SOC stock of A horizons declined after the conversion from forest to cropland or pasture (−17.0 and − 13.6 Mg/ha), from pasture to cropland or forest (−6.2 and − 4.7 Mg/ha), from prairie

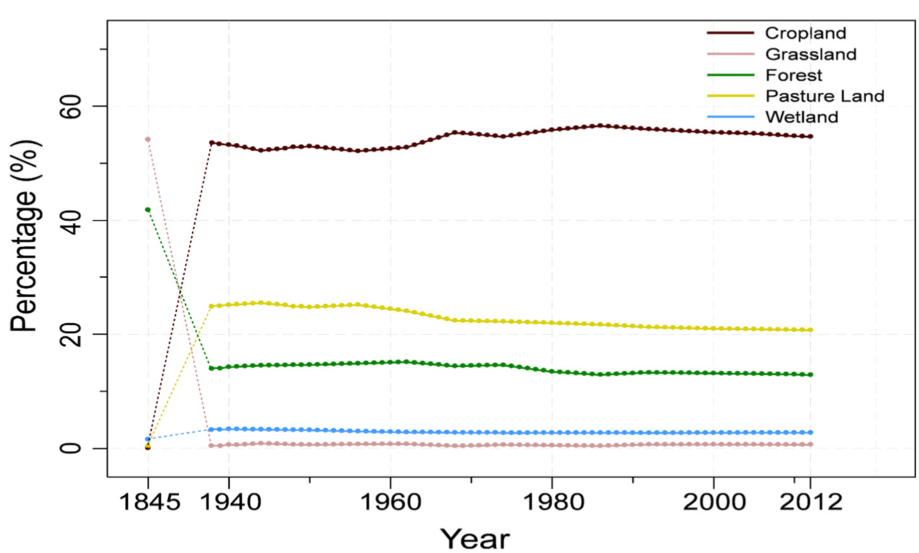

Fig. 2. Changes in the area of land use/land cover (LULC) in 1845 and annually from 1938 to 2012 in Illinois, USA. The LULC data from 1938 to 2012 were obtained from the United States Geological Survey (USGS), and the LULC in 1845 were from the Illinois State Geological Survey (ISGS) published dataset.

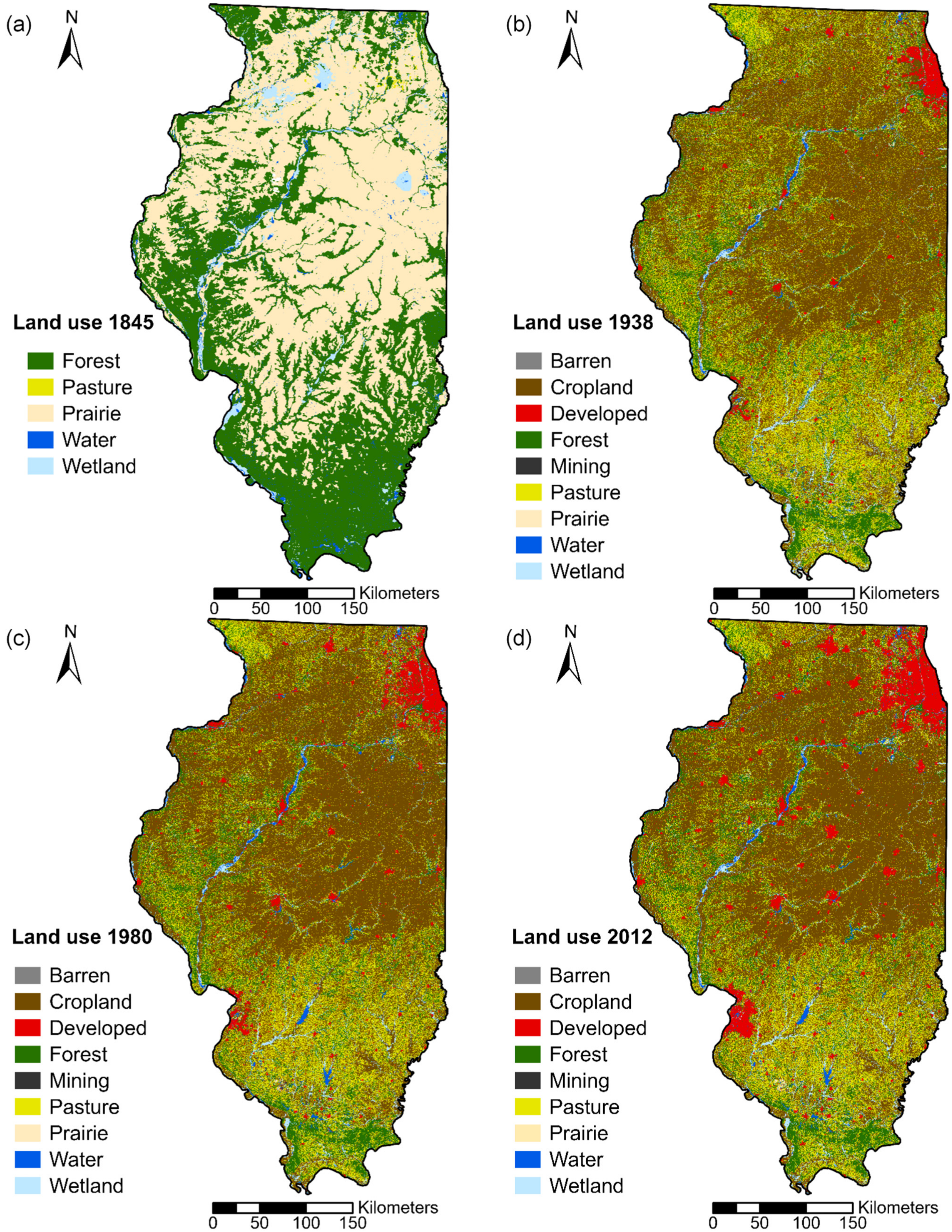

Fig. 3. Land use and land cover (LULC) in Illinois, U.S.A. in (a) 1845, (b) 1938, (c) 1980 and (d) 2012.

to cropland, forest or pasture (−12.8, −11.0 and − 12.5 Mg/ha) and from wetland to cropland, forest or pasture (−14.8, 11.9 and − 12.6 Mg/ha) (Table 3). Similar declines in SOC stocks also occurred for the 0–30 cm layer, but at a 3- to 7-fold greater intensity. Although a relatively minor area, land use changes from forest to wetland (1.8 %) and from pasture to prairie (<0.01 %) entailed increases of +12.8 to 26.3 Mg/ha SOC

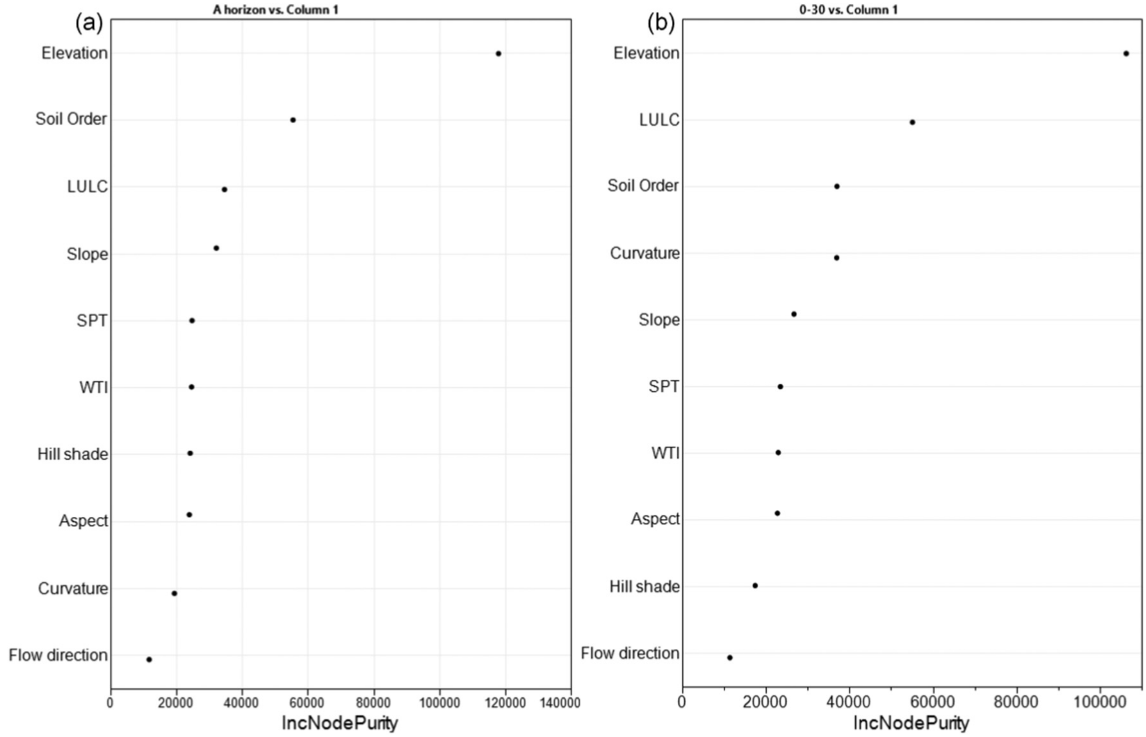

Fig. 4. Variable importance of the random forest model developed for the period of 1980–2012. IncNodePurity means a total decrease in node impurities from splitting on the variable averaged over all trees and is measured by the residual sum of squares.

for A horizon and +41.1 to 70.7 Mg/ha SOC for the 0–30 cm depth layer.

The largest decrease of SOC stock from 1845 to 2012 occurred in the central and east-central region, originally the Grand Prairie of Illinois (Imlay and Carter, 2012), 99.9 % of which has been converted to agriculture as well as urban development since 1845. A slight increase of SOC stocks over this 167 year time period was identified in the northwest Driftless, the Illinois River and Mississippi River sand plains, and the southern forests. The relative change in SOC stock between 1845 and 2012 (Fig. S1) shows a similar pattern: SOC stocks in central and east-central regions declined by 25–50 % in A horizons and by >50 % at 0–30 cm depth.

4. Discussion

4.1. SOC stocks of horizons versus fixed depth

Understanding SOC stock spatial variation is important in order to target practices that maximize returns on SOC sequestration efforts (Minasny et al., 2017), but this is complicated by whether SOC stocks are inventoried by pedogenetic horizons versus fixed depth. Many evaluations of SOC stocks employ fixed depths, commonly 0–30 cm (Adhikari et al., 2019; Huang et al., 2019) because this is the standard depth used by the Intergovernmental Panel on Climate Change (IPCC) to quantify carbon sequestration in soils (IPCC, 2003). The value of assessing SOC stock by pedogenetic horizons is demonstrated by our study: differences in SOC stocks among soil types are more pronounced if horizons are considered, enabling interpretation of spatial patterns in SOC stocks that reflect soil-forming processes (e.g., recency of glaciation in Illinois). Mixing of soil horizons by fixed depth increments can sacrifice important pedogenetic information, though sampling at fixed depth increments reduces the labor and costs needed to detect carbon stock changes (Grüneberg et al., 2010). Additionally, a fixed depth approach could better reflect tillage in annual crop management, which is typically performed (in Illinois and the greater Corn Belt) to 25 or 30 cm depth. Therefore, at landscape positions where the thickness of the A horizon is less than the depth of tillage, tillage may mix the A horizon with underlying horizons (McKyes, 1985), potentialy diluting SOC concentrations (van Wesemael et al., 2010). Our results also corroborate the value of horizon-based approaches because the thickness of the A horizon is related to soil order (e.g., mollic epidon) that in turn reflects associations of native land cover and soil types, namely prairies developed on Mollisols and forests on Alfisols – a relationship reflected in the ethnopedological terms of “prairie soils” and “timber soils” commonly used by farmers in this region (Fuller, 1923).

Assessing SOC stocks by pedogenetic horizon did not always reduce variability in estimated stocks. Variation in SOC stocks was lower when calculated using the fixed depth of 0–30 cm compared to the A horizon, reflecting A horizons that extend beyond a depth of 30 cm. This is consistent with the finding by VandenBygaart et al. (2007) that SOC stocks calculated by horizon compared to fixed depth increments were less variable in only two of six soil types, presumably due to mixing of depth-variable pedogenetic soil horizons in a fixed-depth approach. By comparing the variability of SOC stock in soil horizons and depth increment, Grüneberg et al. (2010) found that the CVs of SOC stocks in A horizon was greater compared to the upper depth increments, even though the upper depth increments were comprised of material from different horizons with strongly different SOC concentrations. In addition, Palmer et al. (2002) noted that the difference in SOC stocks when sampled by depth as compared to sampling by horizon is primarily due to the marked vertical changes in SOC concentration within the A horizon itself.

The fixed depth approach can be problematic because comparisons of SOC stocks are not being made on the same soil mass basis, meaning that bulk density can drive apparent differences in SOC stocks. As an alternative, the equivalent soil mass (ESM) method of soil sampling has been recommended for assessing changes in SOC stocks (Smith et al., 2020; Ogle et al., 2019; von Haden et al., 2020). This is because the equivalent soil mass approach eliminates variation in bulk density, enabling direct comparisons of SOC stocks. However, there is not yet a standardized soil mass value for the ESM approach, limiting its use for SOC stock comparisons. For example, Gifford and Roderick (2003) proposed 4000 Mg/ha of total dry soil matter (including stones and organic matter) as a standardized

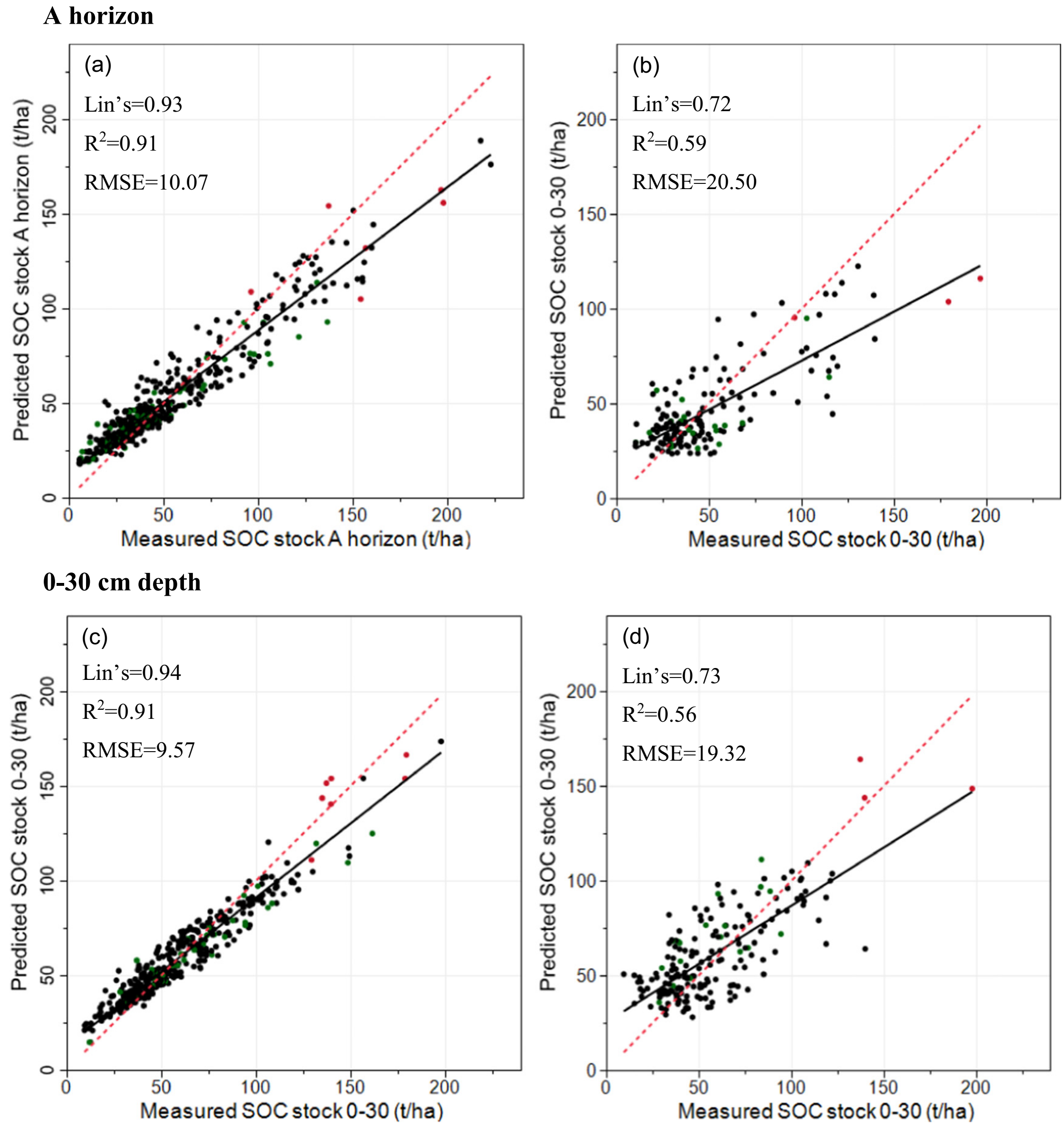

Fig. 5. Relationship between predicted and measured SOC stock (Mg/ha) for A horizon at (a) calibration and (b) validation locations and for 0–30 cm soil depth at (c) calibration and (d) validation locations. Red dots are for values from native remnant prairie and green dots represent the soil under the native remnant forest reported in the peer-reviewed literature.

equivalent mass, whereas Matamala et al. (2008) proposed 1600 Mg/ha of soil mass. A meta-analysis by Rovira et al. (2022) revealed the mass of fine mineral earth to 30 cm depth to be highly variable, ranging from 1500 to >5000 Mg/ha. As a result, when the aim is to compare SOC stocks across sites differing in soil type and/or land use, ESM may not be necessarily advantageous over the fixed depth approach in providing standardized comparisons. To ensure the comprehensiveness of our study, we calculated SOC stocks according to the ESM approach using the average soil (< 2 mm) mass per hectare of 0–30 cm depth (Fig. S1). The high Lin's concordance indices (0.97) show that the SOC stocks calculated by the fixed depth approach are highly similar and thus overall comparable to those obtained by ESM.

4.2. Effects of LULC on SOC stock

Consistent with previous studies, our results identify large declines in surface SOC stock with the conversion of prairie and forest to cropland, consistent with reduced carbon inputs and increased carbon outputs via exacerbated erosion and enhanced mineralization rates (Govaerts et al., 2007; van Wesemael et al., 2010). We found that the dominant land use change of prairie to cropland reduced SOC stock by an average of 12.8 and 42.0 Mg/ha for A horizon and 0–30 cm layer, respectively. These results are broadly consistent with site-specific studies of localized SOC stock change with the agricultural conversion from prairie or forest in Illinois. For example, a recent study by Olson and Gennadiev (2020) in northwestern Illinois found a loss of 24.1 Mg/ha SOC to a depth of 50 cm of the timberland after 150 years of row crops and pasture use. In central Illinois, David et al. (2009) reported that SOC stocks in the 0–20 cm depth of agriculture fields were 21.1 to 52.2 Mg/ha less than the adjacent prairie fields, whereas the reduction of SOC for the pedon (0-100 cm) was 62 to 89 Mg/ha.

Additionally, we found that non-agricultural land use change can elicit changes in SOC stocks comparable in magnitude to converting native vegetation to agricultural use. Specifically, conversion of prairie to forest entailed a reduction of SOC stock that was 11 Mg/ha (A horizon) compared to the loss of 12.8 Mg/ha when converting prairie to cropland. Similarly, Chen and D'Arcy (2016) reported a 35 % decrease of

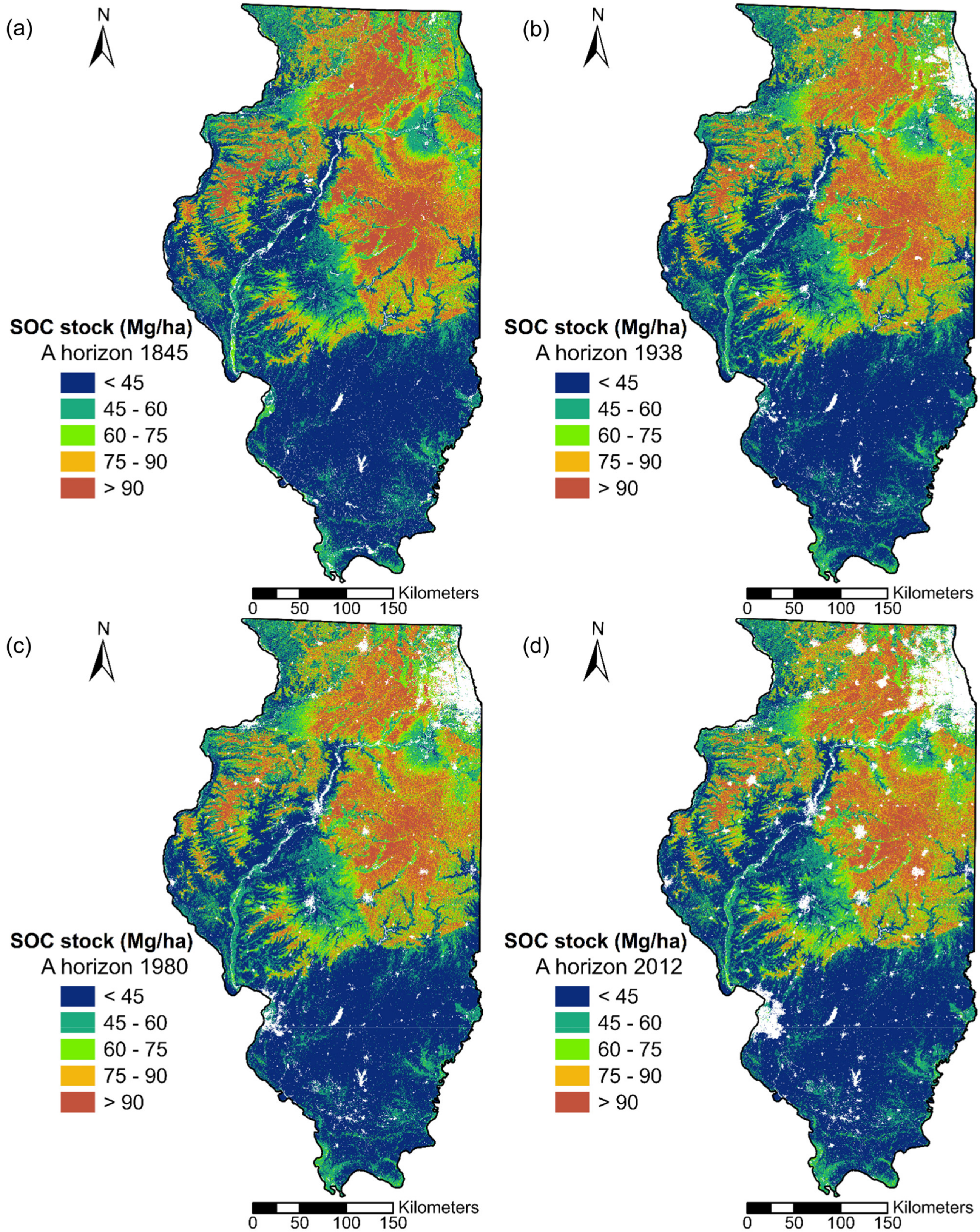

Fig. 6. Predicted A horizon soil organic carbon (SOC) stocks (Mg/ha) of (a) 1845, (b) 1938, (c) 1980 and (d) 2012 in Illinois, USA.

SOC stock at 0-40 cm depth for the conversion from prairie to the deciduous forest in northeastern Illinois. Conversely, the restoration of prairies in the U.S.A. Midwest from agricultural land generally entails recovery of SOC stocks (Matamala et al., 2008). Across the former prairie biome of the central U.S.A., restoring SOC to levels of the original prairies has been estimated to require up to 150 years for fine-textured soils in central Texas (Potter et al., 1999) and up to 230 years for coarse-textured soils in Minnesota (Knops and Tilman, 2000). Higher SOC stocks under prairie

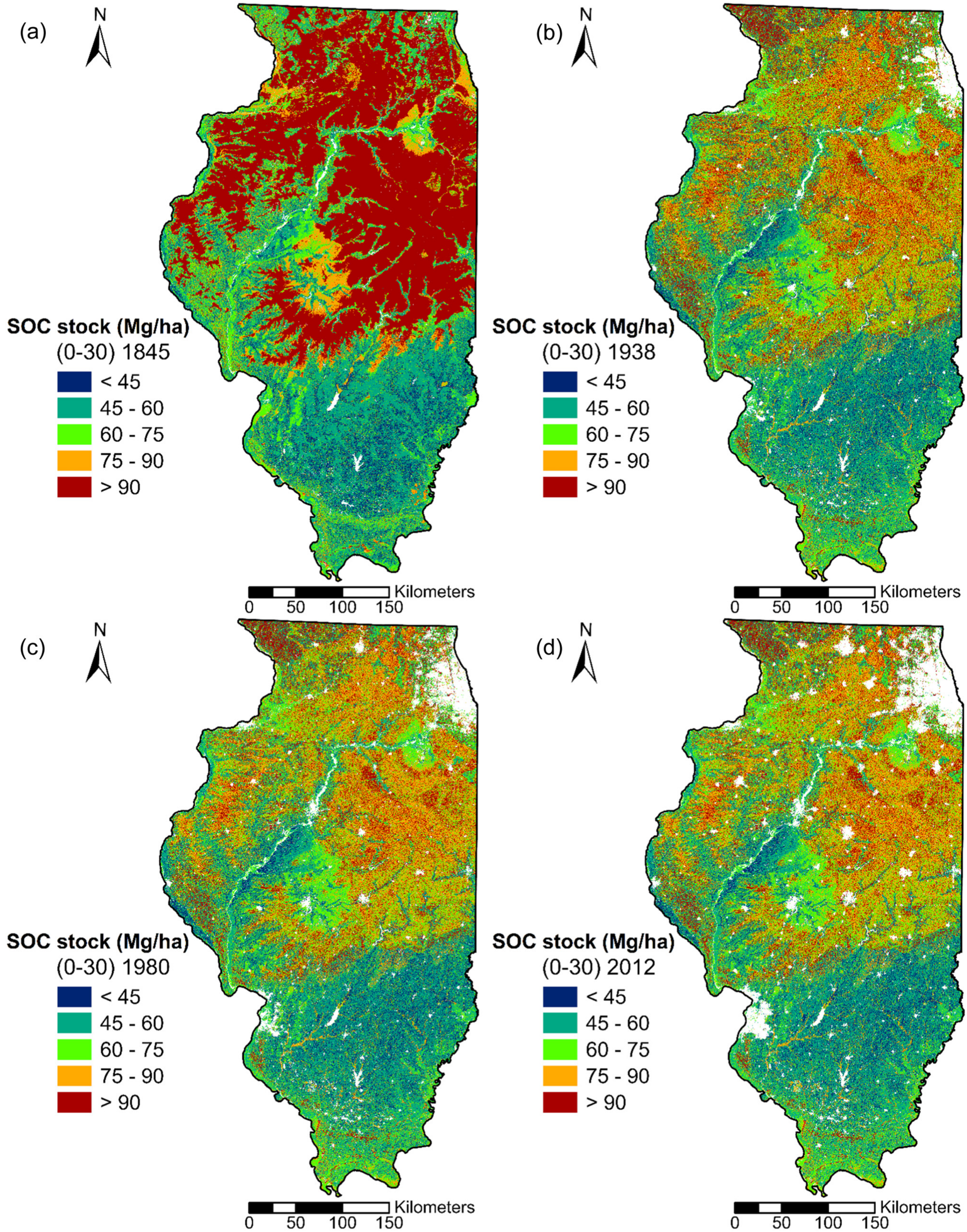

Fig. 7. Predicted 0–30 cm depth soil organic carbon (SOC) stocks (Mg/ha) of (a) 1845, (b) 1938, (c) 1980 and (d) 2012 in Illinois, USA.

are attributed to greater belowground biomass and rate of carbon input: on average, 20 % of annual net productivity of forests is allocated into the belowground parts, 3-fold less than the 60 % invested in grasslands (Heal and Ineson, 1984). Thus, SOC gains with prairie restoration are generally via belowground, root-derived carbon expected to manifest beyond highly superficial depths (e.g., 0–10 cm) (Guzman and Al-Kaisi, 2010).

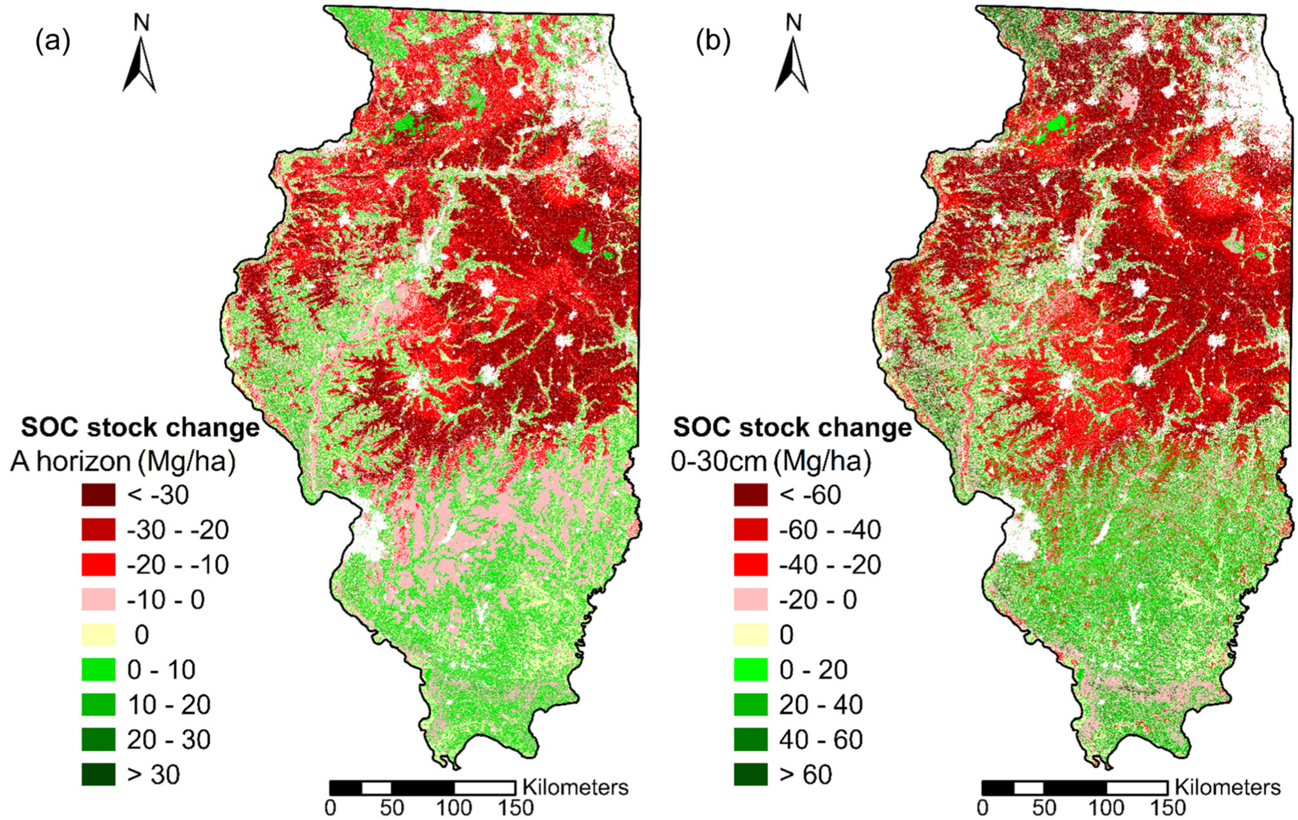

Fig. 8. Soil organic carbon (SOC) stocks (Mg/ha) changes of 2012 relative to 1845 for (a) the A horizon and (b) the 0–30 cm soil depth layer, in Illinois, USA. Note: white areas represent developed areas or water bodies.

4.3. Implications

We find that the majority of soils in Illinois have lost SOC in less than two centuries due to widespread agricultural conversion of prairies and forest, with an estimated mean loss of 60 Mg/ha in surface soils alone. Importantly, estimated SOC loss over the 167 year period modelled (1845–2012) was highly variable across the state, with hotspots of SOC loss concentrated in the central-north region that was originally under tallgrass species in the formerly poorly drained Grand Prairie, mapped largely as Endoaquolls, that is now intensively cultivated and one of the most productive agricultural regions in the world (Iverson, 1988; Imlay and Carter, 2012). Identified hotspots of SOC deficits helps to prioritize and target SOC restoration efforts, either through the restoration of ecosystems and/or agricultural management practices. Assuming native vegetation such as prairie maximizes SOC storage and approaches carbon saturation (Stewart et al., 2008), SOC stocks in 1845 offer a basis for estimating the maximum potential soil carbon sink in what is currently an agriculturally dominated landscape (≈54 % of land area).

Our results corroborate that the conversion of prairies to cropland caused a substantial decline of SOC stocks since the mid-1800s, and that such losses are spatially explicit. This suggests that targeted prairie restoration can inform effective SOC sequestration efforts. Illinois is known as "The Prairie State", as the prairies were the dominant (54 % of land area) vegetation type prior to European settlement in the 1850s. However, by the end of the 20th century, as little as 0.01 % of native prairie remained (Page and Jeffords, 1990). The last major remnant prairie region in the state was the Grand Prairie of east-central Illinois, which for much of the late 19th century was frustrated by high soil saturation and thus the last prairie region transitioned into cultivation with the advent of drainage technologies (Imlay and Carter, 2012). Notably, the high soil saturation of the Grand Prairie and its subsequent drainage for intensive agriculture is also a region of high SOC deficits at surface depths. Restoration of prairies for carbon sequestration in soils would likely benefit from undoing artificial drainage to reestablish the seasonal saturation of soils in this region with historically high SOC stocks.

As for many agriculturally dominated regions with remnant native vegetation, the remaining prairies of Illinois may not necessarily be representative of the majority of the original prairie. These remnant prairies were likely not converted to agricultural use due to poor soil quality, unfavourable drainage and/or slope conditions. Many of the remaining native prairies in Illinois are on soils with very coarse textures, developed on glacial outwash plains and with xeric soil moisture regimes, or on (erodible) hilltops with a lower degree of soil moisture saturation (Baier et al., 1972; Evers, 1955). These prairies are therefore not representative of the mesic prairies developed on sesasonally saturated soils with finer textures (silty clay loam) that dominate the state (Corbett and Anderson, 2006a). Additionally, the cessation of prairie fires means that many remnant prairies – often limited to cemeteries and other small land areas that likely were not sampled in the statewide soil survey – were encroached by fire-susceptible tree species by the mid-20th century (Robertson et al., 1995), thereby changing this land cover to forest.

4.4. Limitations and future study

This study uses existing legacy soil data and various spatially extensive environment covariates to model statistical relationships with surface SOC stocks, and extrapolate estimates spatially and through time. However, the relatively low sampling density could have reduced the model performance, given the difference in R^2 value between calibration (75 %) and validation (25 %) datasets. In addition, the mismatch in scale between soil observations and the pixel of land use data (250 m resolution) can mean that the dominant soil properties of a pixel are not represented by the soil pedon(s) sampled within that pixel (Sanderman et al., 2017). Consequently, regions with low sampling density may be disproportionally

Table 3
Surface soil organic carbon (SOC) stock (Mg/ha) changes from 1845 to 2012 for different combinations of soil order and land use and land cover (LULC), assessed by genetic horizon (A) versus fixed depth (0–30 cm).

A horizon	Area %	Alfisols	Entisols	Inceptisols	Mollisols
Forest → cropland	12.9	−17	−10.3	−15.4	−26
Forest → pasture	12.1	−13.6	−10.6	−11.1	−18
Forest → prairie	0.4	21.4	16.5	12.5	31.4
Forest → wetland	1.8	12.8	9	8.9	22.6
Pasture → cropland	0.1	−6.2	−1.5		−7.8
Pasture → forest	0.02	−4.7	1		−11.3
Pasture → prairie	<0.01	26.3			33.8
Pasture → wetland	<0.01	15.8	18		25
Prairie → cropland	39.4	−12.8	−7.1	−5.3	−26
Prairie → forest	1.9	−11	−3.9	−1	−17.1
Prairie → pasture	8	−12.5	−10.4	0	−18.4
Prairie → wetland	0.3	14.8	12	37	22.3
Wetland → cropland	1.5	−14.8	−11.3	−10.7	−23.6
Wetland → forest	0.2	−11.9	−8.5	−8.9	−18.6
Wetland → pasture	0.2	−12.6	−12.1	−9.9	−15.8
Wetland → prairie	0.01	16.9	8.5	4	31.1

0–30 cm	Area	Alfisols	Entisols	Inceptisols	Mollisols
Forest → cropland	12.9	−36	−26.8	−9.1	−41.5
Forest → pasture	12.1	25.5	18.6	10.1	41.2
Forest → prairie	0.4	42	38	19.4	39.5
Forest → wetland	1.8	41.1	35.4	21.3	35.4
Pasture → cropland	0.1	−31.9	−21.7		−39
Pasture → forest	0.02	−24.3	−13.7		−42.7
Pasture → prairie	<0.01	70.7			52.9
Pasture → wetland	<0.01	53.8	59.3		35.8
Prairie → cropland	39.4	−42	−34.7	−32.4	−44
Prairie → forest	1.9	−35.2	−30.5	−32.5	−42.3
Prairie → pasture	8	23.2	15	−0.5	38.5
Prairie → wetland	0.3	30.9	22.1	−3	26.2
Wetland → cropland	1.5	−37.4	−35.3	−15.1	−40.5
Wetland → forest	0.2	−32.9	−30.2	−11	−35.6
Wetland → pasture	0.2	17.2	4.8	5.2	32.3
Wetland → prairie	0.01	31.5	23.4	2	31.7

influenced by a few data points that may not be representative of the region. Nonetheless, our approach provides finer-scale resolution of this intensively managed region of the world compared to regional Midwest U.S.A. (Thomas et al., 2017) or global estimates (Sanderman et al., 2017).

As demonstrated by our approach, a key obstacle to modelling historical SOC stocks under land covers that are effectively no longer present (i.e., prairie) is the relatively scarce and likely biased SOC measures for native vegetation. The NCSS dataset is a national inventory that compiles pedons from soil surveys conducted largely in agriculturally dominated landscapes of the mid to late 1900s. The lack of soil observations in the 1850s – which predates the earliest soil surveys by at least half a century – either as soil classification or SOC values precludes model validation for SOC backward prediction. Although we included the SOC observation under native prairie (10 observations) and forest (64 observations) from the peer-review publications, more observations would be ideal. Here, meta-analysis of SOC stocks in prairie restoration chronosequences in the greater North-Central U.S.A. could provide an indirect assessment of SOC stocks under pre-agricultural land use. Additionally, changes in LULC of Illinois between 1845 and the early 1900s (Walters and Smith, 1992) are not captured by the coarse temporal resolution of LULC maps. Historical documents that provide additional LULC information in the early 1900s would be valuable.

Providing more refined spatiotemporal dynamics of land use and land cover would likely improve the accuracy of backcasting, such as the spread of tile drainage beginning in the late 19th century that today dominates the regions of Illinois that our study identifies as having the largest surface SOC deficit (Imlay and Carter, 2012). However, the extent and location of tile drainage in Illinois and the Midwest is largely unknown since records are kept by private landowners (Kalita et al., 2007; Beauchamp and Pavelis, 1987). Remote sensing approaches are improving the current detection of tile drainage today (Valayamkunnath et al., 2020), but not historical drainage trends and locations. The role of tile drainage on SOC, in particular subsoil SOC (Castellano et al., 2019), is likely to improve estimates of SOC dynamics over the past 150 years of agricultural intensification in the Midwest. Soil erosion is likely to redistribute SOC with the agricultural conversion of native vegetation (Olson et al., 2016), leading to appreciable changes in observed SOC stocks at the location of erosion (van Wesemael et al., 2010) but also increases in SOC at recipient landscape positions (Veenstra and Lee Burras, 2015). We found that variables related to soil movement (e.g., elevation, slope) had a substantial influence on modeled SOC stocks, also suggesting that surface SOC distribution in Illinois could be highly related to soil erosion/deposition phenomena. The dearth of statewide soil erosion data, however, limited the estimation of the erosion-induced and topography-related variability in SOC stocks at the regional scale. As the fate of SOC that is redistributed through erosion remains debatable (Sanderman and Berhe, 2017), considering the impact of historical erosion and quantifying potential redistribution of SOC stocks due to erosion processes would benefit SOC assesments over time.

5. Conclusion

We evaluated spatially explicit distribution and changes in surface SOC stocks on a pedogenic and fixed depth basis in Illinois across 167-years of LULC using the space-for-time substitution method. Using DEM-derived topographic attributes, LULC and soil type as environment covariates, we develop an RF machine-learning algorithm to quantify the spatial relationship between measured SOC with environment covariates. The spatial variation of SOC stock was mainly affected by LULC and soil type (USDA taxonomy), with SOC stocks being highest under prairie and lowest under pasture. Though SOC stocks varied less by soil type than by land use, surface SOC stocks were greatest in Mollisols and least in Alfisols. Our approach revealed differences in net SOC change that further varied by land use depending on whether genetic horizons (A) or fixed depth (0–30 cm) were used, which was consistent with the extent of soil types and variation in A horizon depth. A general decrease in SOC stocks between 1845 and 2012 in Illinois occurred due to land conversion from prairie and forest to agriculture. While approximately 25 % of SOC has been lost in surface soils alone since European settlement and agricultural intensification, this large SOC deficit signifies an opportunity to sequester carbon in this agriculturally dominant region by management practices or restoration of native vegetation, in particular for poorly drained Mollisols of east-central Illinois.

CRediT authorship contribution statement

Nan Li: Conceptualization, Methodology, Writing - Original draft preparation.
Shengnan Zhou: Data curation, Statistics, Reviewing.
Andrew J. Margenot: Conceptualization, Supervision, Writing, Reviewing.

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2022.159038.

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