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High soil carbon sequestration rates persist several decades in turfgrass systems: A meta-analysis

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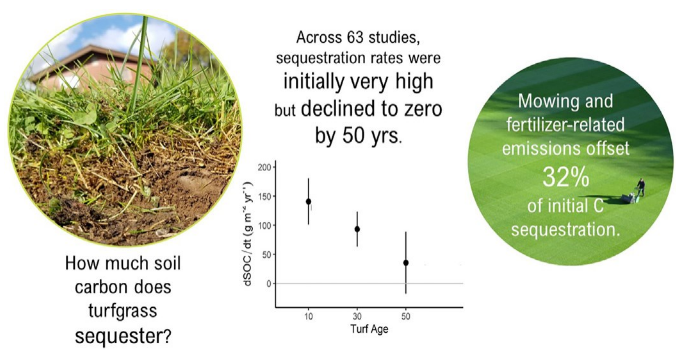
HIGHLIGHTS

- Turfgrass can sequester C and may influence emissions stemming from urbanization.
- We summarized soil C sequestration rates from 63 datasets, most in the U.S.
- Initial C sequestration exceeded rates for many soil conservation practices.
- On average turfgrass stopped accruing soil C by 50 years after establishment.

GRAPHICAL ABSTRACT



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ABSTRACT

Managed turfgrass is a common component of urban landscapes that is expanding under current land use trends. Previous studies have reported high rates of soil carbon sequestration in turfgrass, but no systematic review has summarized these rates nor evaluated how they change as turfgrass ages. Here we conducted a meta-analysis of soil carbon sequestration rates from 63 studies globally, comprised mostly of C3 grass species in the U.S., including 24 chronosequence studies that evaluated carbon changes over 75 years or longer. We showed that turfgrass established within the last ten years had a positive mean soil C sequestration rate of 5.3 Mg CO_2 ha^{-1} yr^{-1} (95% CI = 3.7–6.2), which is higher than rates reported for several soil conservation practices. Areas converted to turfgrass from forests were an exception, sometimes lost soil carbon, and had a cross-study mean sequestration rate that did not differ from 0. In some locations, soil C accumulated linearly with turfgrass age over several decades, but the major trend was for soil C accumulation rates to decline through time, reaching a cross-study mean sequestration rate that was not different from 0 at 50 years. We show that fitting soil C timeseries with a mechanistically derived function rather than purely empirical functions did not alter these conclusions, nor did employing equivalent soil mass versus fixed-depth carbon stock accounting. We conducted a partial greenhouse gas budget that estimated emissions from mowing, N-fertilizer production, and soil N_2O emissions. When N fertilizer was applied, average maintenance emissions offset 32% of C sequestration in recently established turfgrass. Potential emission removals by turfgrass can be maximized with reduced-input management. Management decisions that avoid losing accrued soil C—both when turfgrass is first established and when it is eventually replaced with other land-uses—will also help maximize turfgrass C sequestration potential.

Abbreviations: ESM, equivalent soil mass; FD, fixed depth; SOC, soil organic carbon; GHG, greenhouse gas.

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1. Introduction

Turfgrass has been estimated to cover almost 2% of land area in the U.S. (Milesi et al., 2005) and its extent will likely increase with the growth of urban, suburban, and exurban land uses. Within developed landscapes, turfgrass commonly occupies spaces between built structures, where it provides a surface for recreation, aesthetic value, and a variety of functional components. One of these functional components is carbon (C) sequestration (Morgan et al. 2010; Pouyat et al., 2009; Pouyat et al., 2006; Zirkle et al., 2011). Turfgrass is usually perennial, grows rapidly, and is known for having an active root system that contributes significantly to accumulation of soil organic carbon (SOC, Qian et al., 2010). However, maintaining high quality turfgrass is reliant on repeated cultural practices like mowing, irrigation, and fertilization. The fossil fuel consumption associated with turfgrass maintenance and N_2O emissions from nitrogen fertilization could offset—at least partially—the SOC sequestration benefits of turfgrass (Gu et al., 2015; Selhorst and Lal, 2013; Tidåker et al., 2017; Townsend-Small and Czimczik, 2010).

Quantifying the greenhouse gas emissions of turfgrass is one important component of understanding the climate impacts of urbanization, which are poorly constrained (Moran et al., 2018). A dominant trend over the last 70 years has been the displacement of agricultural land with suburban and exurban uses (Brown et al., 2005). In the U.S., about two-thirds of agricultural lands—broadly defined as croplands, managed forests, and managed rangelands—that were converted to other land uses from 2001 to 2016 were converted to low-density residential development (Freedgood et al., 2020). This kind of development, also referred to as exurban land use in the U.S., impacted an area of 7.3 million acres. Turfgrass is particularly prevalent in low-density residential development (Boone et al., 2010; Currie et al., 2016), and thus agriculture-to-turfgrass land use conversion is one important dynamic that occurs in urbanizing landscapes.

Within the context of emerging C markets and climate legislation, determining the climate impacts of turfgrass is also relevant for uncovering potential liabilities and opportunities for the turfgrass industry. The U.S. turfgrass and lawncare industry was estimated to generate \$57.9 billion in income in 2002 (Haydu et al., 2006), an amount equivalent to \$92.5 billion in 2022 dollars. Existing research has shown considerable potential for residential lawns and golf courses to accumulate SOC (Qian et al., 2010; Qian and Follett, 2002; Selhorst and Lal, 2011; Selhorst and Lal, 2013). However, there has not yet been a systematic review of the topic, and significant knowledge gaps remain around the emissions from turfgrass over its entire lifecycle. With few exceptions, previous studies have not considered the emissions from land-use change when turfgrass is newly established (Selhorst and Lal, 2013), and the extent to which emissions change through time as turfgrass systems mature (Shi et al., 2012).

Many previous studies have estimated a single rate for SOC sequestration in turfgrass, and have not addressed the ecological theory of SOC dynamics, which predicts that SOC accumulation diminishes over time as plant inputs and SOC decay reach a dynamic equilibrium (Caruso et al., 2018; Falloon and Smith, 2009). Despite some exceptions (Carley et al., 2011; Selhorst and Lal, 2013; Shi et al., 2012), studies that measured SOC sequestration rates seldomly report the timespan over which potential SOC sequestration rates could hold. Carbon accounting efforts frequently neglect the finite nature of SOC accumulation (Poulton et al., 2018) and the importance of assessing current SOC stocks in relation to historic values (Sanderman and Baldock, 2010), not only within turfgrass research but across managed soils more broadly.

However, the turfgrass and urban ecology research communities have amassed data that allow changes in SOC sequestration to be evaluated over multiple decades. These communities have conducted a considerable number of chronosequence studies—sampling unique turfgrass sites, which were established at different times across a region, and provide a large range of sample ages within the region. Using these data, chronosequence studies evaluate SOC stock changes through time by applying a space-for-time substitution. Despite limitations to the chronosequence approach (namely that different locations do not have identical management and environmental settings) it can be employed rapidly in one or two field seasons and can be used to evaluate SOC dynamics across much longer time periods than would typically be possible with repeated sampling. Turfgrass chronosequences have been evaluated in at least 29 locations across the United States and New Zealand (Fig. 1), and 80% of these studies covered age ranges of 75 years or more. This collective dataset is arguably unique in documenting long-term SOC changes for a single vegetation type across a large range of climatic conditions.

In the present study, we aimed to synthesize these chronosequences and other repeated measures studies to characterize long-term SOC changes in turfgrass systems, and to evaluate the factors that caused studies to differ from each other. We conducted a systematic review and meta-analysis to answer the question: Is turfgrass, on average, a net source or sink of C after 10, 30, and 50 years post-establishment? Using meta-regression we evaluated how prior land-use, climate region, turfgrass photosynthetic pathway (C4 verses C3), turfgrass use (putting greens, athletic fields, small research plots, lawns, and roughs), and study methodology (chronosequence versus repeated-measures) influenced SOC sequestration rates. Because most authors described SOC changes through time using linear or polynomial regressions, we also refit these datasets using an exponential rise-to-maximum function that is characteristic of mechanistic models of SOC dynamics (Caruso et al., 2018). We tested the hypothesis that fitting timeseries with a mechanistically-derived model would lower estimates of SOC sequestration in mature turfgrass. Finally, we also estimated emissions (CO_2 and N_2O) from mowing and N fertilizer use to compute potential net GHG emissions from turfgrass through time.

2. Methods

2.1. Literature search and dataset development

We conducted a systematic review from Nov 2020 to Jan 2021 using Google Scholar, Web of Science, and the Turfgrass Information File Database. The search terms targeted were "soil carbon", "carbon sequestration", "carbon storage", or "carbon stock", with "turf", "turfgrass", "lawn", "urban ecosystem", "residential", "Fescue", "Zoysia", "Poa", "Cynodon", "Bouteloua", "Lolium", or "Agrostis". We included only peer-reviewed studies written in English that measured SOC change over one year or longer, and where grass was managed as turf (mowed or clipped regularly). We included studies that sampled to any soil depth, and included several methodologies: small-plot research conducted over a few years (22 datasets from 4 articles, citations detailed in Table S1), chronosequences of golf courses or residential lawns (39 datasets from 16 articles), and one study that was a variation on a chronosequence method and compiled long-term soil test data provided by golf courses of various ages (3 datasets from Qian and Follett, 2002). In total, 63 datasets from 21 articles met the search criteria.

We excluded 1) duplicate reports of the same data, 2) small plot studies that did not report baseline SOC stocks, and 3) pure modeling studies. We included five papers that only measured changes in SOC concentrations, but not areal stocks (i.e., SOC in Mg ha^{-1}). For these papers, we converted from concentrations to stocks using several approaches. For two papers (Law and Patton, 2017; Qian and Follett, 2002) we used estimated bulk densities provided by the authors. For the chronosequences reported in Selhorst and Lal (2011), we used the average bulk density reported by the author. For the 13 choronosequences reported in Selhorst and Lal (2013), we estimated bulk density from the average relationship between percent C and bulk density reported by Selhorst (2011). For Wang et al. (2014), we used bulk density values from official soil survey descriptions.

The effect sizes summarized in the meta-analysis were the rates of change in SOC stocks (dSOC/dt, where t is turfgrass age) for three time periods: 1–10 years, 30 years, and 50 years post-establishment, denoted as $dSOC_{1-10}$, $dSOC_{30}$, and $dSOC_{50}$, respectively. The $dSOC_{1-10}$ dataset pooled results from small-plot studies that all had durations of 4 years or less, and from chronosequence studies, for which we computed dSOC/dt at t = 10 years. Thus, $dSOC_{1-10}$ operationally represents recently established turfgrass, with a range in ages.

Fig. 1. Map of study locations. Sixty-three datasets from 22 manuscripts met the search criteria (see full citation list in the Supplemental Information).

Small plot studies reported dSOC/dt as a difference between repeated measurements divided by elapsed time. The chronosequence studies all reported continuous functions fitted to SOC(t) over multiple-decade timespans (Fig. 2A). The various author teams employed several types of equations to describe SOC(t), including linear, polynomial, and rational models (Table S1 and Fig. 2A). All these equation forms were readily differentiated to derive equations for dSOC/dt (Fig. 2B). We evaluated dSOC/dt at t = 10, 30, and 50 by transforming the author's reported regression parameters.

However, most studies did not report standard errors for regression parameters or provide sufficient information to compute them. Therefore, all the chronosequences had to be reanalyzed in order to re-calculate the regression parameters and their associated errors, in order to compute uncertainties for dSOC/dt. In most cases, the original data were obtained from the authors of the studies. If authors did not reply after two inquiries, or no longer had access to the data, we captured data from published figures using WebPlotDigitizer (Rohatgi, 2021). We computed standard errors for the transformed regression parameters by applying a Taylor approximation with the delta method as implemented by the R 'msm' package (Jackson, 2011). We used the standard errors of dSOC/dt as measures of precision to weight each study in the meta-analysis.

For articles where original data could not be obtained from authors or figures, missing standard errors were imputed as 10% of the mean value for dSOC/dt, as proposed by Luo et al. (2006) and employed by others (Meurer et al., 2018; Nunes et al., 2020). This approach for imputing error was used for 18 datasets from 4 articles, or 29% of all the datasets. Most of the studies with missing standard errors (17 of 18) were small-plot trials; therefore, it is noteworthy that the imputed error estimates primarily impacted results for $dSOC_{1-10}$.

To assess factors influencing SOC change, we coded each study for prior land use (cropland, forest, shrubland, unmanaged grassland, managed pasture or turf, and desert), Köppen climate region, photosynthetic pathway ('cool season' = C3, or 'warm season' = C4), and study methodology (chronosquence or repeated measurements). Studies were also coded for turfgrass use (athletic fields, putting greens, fairways, lawns, roughs, and small research plots). Small research plots were coded as a unique group because most studies did not indicate the real-world use the plots were managed for. Photosynthetic pathway was determined from the dominant turfgrass species reported by authors. For studies not providing this information, we defined the photosynthetic pathway as C3 for the northern US climates, C4 for the southern US climates, and an equal prevalence of C3 and C4 in transitional regions. The prevalence of C3/C4 turf species determined by Trammell et al. (2019) for seven U.S. cities was also used (see Table S1).

2.2. Re-analysis of chronosequences

The chronosequence datasets were all re-analyzed by: 1) computing areal stocks for SOC from concentration data, if necessary, 2) fitting regressions to SOC(t) employing the same functional forms employed by the authors, and 3) transforming the regression coefficients to compute dSOC/dt at t = 10, 30, and 50 years, and to calculate standard errors for dSOC/dt. In some cases, data extracted from figures produced regression parameters with minor discrepancies from the author's reported regression parameters. In these cases, we used the authors' parameters as mean values for the meta-analysis, weighted by the standard errors we computed as a best-we-can-do estimate.

Steps 2) and 3) were applied first to compute SOC(t) and dSOC/dt for individual soil layers, and then SOC stocks were summed across all depths to compute SOC(t) and dSOC/dt for the whole measured profile. In cases where authors did not report regressions for total SOC(t) we applied the same equation types they employed for individual soil layers. If the authors used more than one equation type for different layers, or there was a poor fit, we followed a model selection process. Outcomes of fitting decisions for each study are in Table S1. We employed a principle of replicating the methods employed by the original authors to the extent possible, balanced by selecting reasonable and parsimonious regression models. We evaluated linear, quadratic, and third order polynomial fits, and selected the best model based on Akaike information criterion (AIC) values with a preference for lower-order models when AIC values were similar.

All studies originally employed fixed depth (FD) sampling to determine SOC stocks. However, for studies that provided bulk density and SOC concentrations for individual depth intervals (N = 16), we re-analyzed carbon stocks on an equivalent soil mass (ESM) basis. The ESM accounting approach considers the fact that bulk density is likely to decrease with time since turfgrass establishment, due to increases in soil organic matter and root biomass. Changes in bulk density can have complex effects on SOC stock computations (Sollins and Gregg, 2017; von Haden et al., 2020; Xiao et al., 2020). However, one reasonable expectation is that SOC stocks would be over-estimated by FD sampling in older turfgrass, because cores collected to a fixed depth intercept more of an aggrading verdure (thatch layer) or A horizon soil that is enriched in SOC and encounter less subsurface soil that is depleted in SOC. We recomputed SOC(t) using the youngest turfgrass plots as a reference condition. We calculated SOC stocks at all other timepoints to the same mass of soil encountered in the reference plot cores. ESM computations were implemented using the method and R code provided by von Haden et al. (2020), which fits splines to cumulative SOC stocks versus cumulative soil mass relationships for each soil core. We allowed extrapolation past the deepest measured depth in cases where less

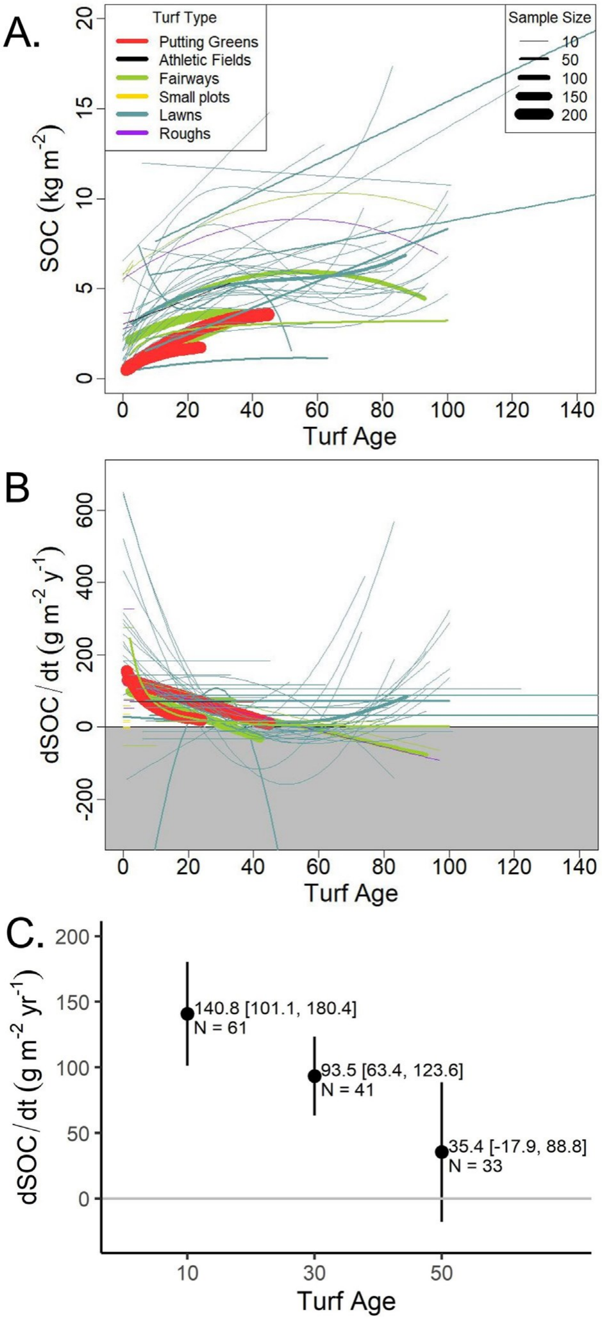

Fig. 2. Turfgrass SOC stock changes through time based on authors' equations. (A) Total SOC stocks versus turfgrass age for all studies. Line thickness indicates study sample size and line color indicates turfgrass use. Note that trends for short-duration, small-plot studies are shown as short segments near t = 0 years. (B) Annual rate of SOC gain or loss, dSOC/dt, for all studies. (C) Meta-analysis mean and 95% confidence intervals for $dSOC_{1-10}$, $dSOC_{30}$, and $dSOC_{50}$.

soil was encountered in a core compared to the reference. For meta-analysis of $dSOC_{1-10}$, $dSOC_{30}$, and $dSOC_{50}$, we pooled ESM-based calculations for the 16 studies that provided sufficient data, and FD-based calculations for the remaining studies.

As an additional exercise, we also re-fit all the chronosequence studies with an exponential rise-to-maximum model that follows from a mechanistic perspective of SOC dynamics (Caruso et al., 2018). The linear, quadratic, and polynomial regression models originally used are empirical and not tied to any mechanistic model. Mechanistic SOC models incorporate concepts of C inputs, decay, and selective stabilization that drive changes in pool sizes over time until a dynamic equilibrium is reached (Falloon and Smith, 2009). Caruso et al. (2018) proposed the following equation to describe SOC(t):

$$SOC = a - he^{-ct} \qquad (1)$$

where a is the equilibrium SOC stock, and c equals the sum of intrinsic rates of SOC gains from biomass inputs and losses through decay. Parameter c controls the velocity with which SOC approaches equilibrium. The parameter h reflects rates of SOC gains and losses as well as initial conditions (baseline SOC stocks relative to the equilibrium SOC stocks). When h is positive (meaning baseline SOC < equilibrium SOC) SOC increases through time. This model is mathematically similar to a one-pool model of SOC decay, but explicitly avoids assumptions about the number of discrete pools that SOC is composed from. We fit Eq. (1) to SOC timeseries using the 'nls' function in the R base package (R Core Team, 2020) as demonstrated by Caruso et al. (2018).

2.3. Meta-analysis

To summarize $dSOC_{1-10}$, $dSOC_{30}$, and $dSOC_{50}$ across studies, we employed a random effects meta-analysis model. We used a random effects model because multiple climate regions, turfgrass species, and turfgrass uses were represented among the studies. We used the inverse variance method to weight each study (variance = SE^2). We evaluated between-study heterogeneity by computing heterogeneity variance (τ^2), performing a Q-test, and evaluating Higgins' I^2 (where I^2 > 75% was considered high heterogeneity). We checked for influential cases using Baujat plots and externally standardized residuals as influence diagnostics (Harrer et al., 2022). Where high-influence studies were detected, results are reported both with and without the studies included.

Sub-group analyses were performed to assess whether studies differed based on prior land use, climate region, turfgrass photosynthetic pathway, turfgrass use, and study methodology. Each potential explanatory variable was evaluated individually as a categorical variable in a mixed-effects model, and the ability of the variable to explain between-study heterogeneity was evaluated by a Q-test (Harrer et al., 2022). Additionally, linear meta-regression was used to evaluate possible relationships between dSOC/dt and maximum soil sampling depth.

2.4. Partial GHG budget analysis

We constructed partial GHG budgets for each dataset that considered dSOC/dt, CO_2 emissions from mowing, CO_2 emissions from the production and distribution of N-fertilizer, and soil N_2O emissions resulting from application of N fertilizer. We did not account for CO_2 emissions related to irrigation. We recognize that irrigation is an important emissions source (McCarthy et al., 2020; Rothausen and Conway, 2011). However, irrigation rates and their CO_2 emissions are difficult to estimate. Residential irrigation practices do not correspond well with local climate (Groffman et al., 2016), few water districts provide GHG accounting (The Climate Registry, 2020), and representative values for the GHG intensity of irrigation are not readily available, as the extraction, conveyance, and treatment of irrigation water are regionally-specific (Bauer et al., 2014; US EIA, 2022). Therefore, a robust assessment of irrigation-related GHG emissions was considered beyond the scope of this study. Emissions associated with herbicides and pesticides were previously estimated to account for <8% of turfgrass maintenance-related emissions (Braun and Bremer, 2019; Selhorst and Lal, 2013), and were not included here.

Two scenarios were considered: 1) an unfertilized scenario, reflecting the fact that 28–49% of households in 6 major U.S. metropolitan areas report not fertilizing lawns (Groffman et al., 2016), and 2) a N-fertilized scenario, in which N was assumed to be applied in the form of urea, and N-fertilizer requirements were calculated for each location from a temperature-based growth potential model used by some professional turf managers (Gelernter and Stowell, 2005; PACE Turf, 2022; Woods, 2013).

For each dataset, annual net GHG emissions (GHG_{net}) were calculated as follows, with all emissions sources expressed as CO_2-equivalents:

$$GHG_{net} = Mowing + N\,fertilizer\,production + N_2O\,emissions - dSOC/dt \quad (2)$$

Both mowing frequency and N-fertilizer rates were estimated using the temperature-based turfgrass growth potential model, following Soldat et al. (2020). This model computes the relative growth potential of turfgrass as (Gelernter and Stowell, 2005):

$$\text{Relative growth potential} = e^{-0.5\left(\frac{T_{avg}-T_{opt}}{V}\right)^2} \quad (3)$$

where T_{avg} is the average monthly temperature (°C), T_{opt} is the optimum growth temperature (20 °C for C3 turfgrasses and 31.1 °C for C4 turfgrasses), and V is a variance constant (set to 5.5 for C3 and 7 for C4 turfgrasses, Woods, 2013). T_{avg} was determined for each study location from monthly average temperature for 1981–2010 (NOAA, 2022). This modeling approach implicitly assumes that rainfall or irrigation was sufficient, and that turfgrass growth was only limited by temperature.

We applied a calendar mowing schedule, following the minimum mowing frequencies for different turfgrass types during periods of optimum growth shown by Soldat et al. (2020): once weekly for lawns and roughs, twice weekly for fairways and warm-season (C4) athletic fields, and three times weekly for putting greens. We also moderated mowing frequency by turfgrass growth rate and assumed the suggested mowing frequency when relative growth potential exceeded 75 %, three-quarters of the suggested frequency when growth potential was between 50 and 75 %, half the suggested frequency when growth potential was between 20 and 50 %, and no mowing when growth potential was ≤20 %.

For athletic fields, putting greens, and roughs, we assumed the same professional mowing equipment and fuel consumption rates as Soldat et al. (2020), and converted diesel and gasoline volumes to CO_2 emissions using EPA conversion factors (US EPA, 2022). Mowing equipment emissions for athletic fields were computed based on a Toro Groundmaster 4300D with an emissions factor of 8.32 kg CO_2 ha^{-1}; putting greens were computed based on a Jacobsen Eclipse 322 hybrid gasoline reel mower with an emissions factor of 3.20 kg CO_2 ha^{-1}, and fairways and small research plots were computed based on a John Deere 7500A fairway mower with an emissions factor of 2.26 kg CO_2 ha^{-1} (Soldat et al., 2020). Because most studies of lawns were of residential lawns, we assumed a gasoline push-mower with an emissions factor of 15.88 kg CO_2 ha^{-1}, based on Velasco et al. (2021) who calculated emissions factors for 5 different models of push mowers.

For the fertilized scenario, we estimated N-fertilizer requirements by multiplying monthly growth potential by a maximum monthly N use of 1.5 g N m^{-2} for Festuca species, 3.5 g N m^{-2} for other C3 species, and 4 g N m^{-2} for C4 species, based on recommendations by Woods (2013). Maximum nitrogen use rates are site-specific, and assumed values are intended to be tailored to local conditions and turf species when employed as part of a nutrient management program; however, these baseline values are suggested as a starting point (PACE Turf, 2022; Woods, 2013). Estimated nitrogen requirements based on the growth potential model are shown in Table S2. We computed the CO_2 emissions from the production of N-fertilizer by applying an emissions factor of 3.781 kg CO_2 kg N^{-1}, which was estimated for North American production of urea (46–0–0) fertilizer (Haxha and Christensen, 2018).

We estimated N_2O emissions for the fertilized scenario by assuming an emissions factor of 1% of fertilizer-N applied was lost as N_2O (IPCC, 2019). N_2O emissions for the unfertilized scenario were estimated as 0.15 g N_2O-N m^{-2} yr^{-1}, which was the average emissions rate from unfertilized turfgrass reported in a review of turfgrass studies by Braun and Bremer (2018). We applied a 100-year sustained global warming potential value of 270 to convert N_2O emissions to kg CO_2-equivalents (Neubauer and Megonigal, 2015).

We computed cross-study mean GHG_{net} using a meta-analysis approach, with the standard error of dSOC/dt as a weighting factor. Thus, uncertainties in dSOC/dt but not from fertilizer, N_2O, or mowing emissions were propagated to mean GHG_{net} estimates.

3. Results

The datasets meeting the search criteria were located primarily in the United States, with one study each in New Zealand and Chile (Fig. 1). We note that research from under-represented areas were found in the search but did not meet criteria for inclusion, including studies from Australia (Riches et al., 2020; van Delden et al., 2016), Europe (Tidåker et al., 2017), Russia (Sarzhanov et al., 2015), and Asia (Kong et al., 2014; Ng et al., 2015; Velasco et al., 2021).

3.1. Meta-analysis of authors' equations

Relationships between SOC stocks and time since turfgrass establishment showed a general increase over the first 30 to 50 years, with stocks leveling-off or declining thereafter (Fig. 2A). The regressions shown are authors' original functions, with the exception that SOC stocks were recomputed using equivalent soil mass (ESM) accounting where sufficient data were provided (N = 16 datasets). A notable feature of the datasets is the large range in baseline SOC stocks that can be observed at t = 0 years (Fig. 2A). This reflects differences in sampling depth among studies, which ranged from 5 to 100 cm, although most datasets sampled to 15 or 30 cm depth. It also reflects the large range in climatic regions and various prior land uses represented.

Also notable was that one-third (14) of the 42 studies that captured multi-decadal dynamics modeled SOC(t) with linear regression models. The linear model suggested consistent growth in SOC stocks through time and a constant SOC sequestration rate, and deviates from mechanistic theory predicting that SOC stocks level off to a steady-state value. Five of these studies had small sample sizes (≤5 locations sampled) and thus authors may have chosen a linear model for lack of data, but 8 studies with large sample sizes demonstrated linear increases in SOC stocks over multiple decades.

Among studies that modeled SOC(t) with non-linear regressions, many authors applied third-order polynomial regressions (Fig. 2A). When these equations were differentiated to determine annual SOC sequestration rates they translated to quadratic functions (Fig. 2B). These quadratic functions were inconsistent with SOC dynamic theory because they produced local minimums midway into time series. They suggested minimum SOC sequestration rates were reached at 30–50 years and increased thereafter, rather than staying at a low steady-state value. Because these local minimums were likely artifacts of convenient regression choices, and because increasing sequestration rates in decades-old, consistently managed, perennial systems have not been reported elsewhere, we conducted meta-analysis on rates of SOC change only up to 50 years, the point at which sequestration rates in most studies reached a minimum (Fig. 2C).

The cross-study mean SOC sequestration rate for recently established turfgrass ($dSOC_{1-10}$) was 141 g C m^{-2} $year^{-1}$ [95% CI 101; 180], equivalent to an atmospheric CO_2 removal of 5.28 Mg CO_2 ha^{-1} $year^{-1}$ [3.71; 6.17]. This result was based on 61 datasets, with 2 highly influential datasets removed (Selhorst 2013-Las Vegas and Acuna 2017-Cochise, Table S1). (Result with all studies included was 158 g C m^{-2} yr^{-1} [95% CI 111; 205].) These results indicate that recently established turfgrass was on average a net C sink. However, the between-study heterogeneity variance was very high, estimated at τ^2 = 19,027 with an I^2 value of 95.3 %, indicating large differences in computed sequestration rates among studies. The prediction interval ranged from −125 to 407 g C m^{-2} yr^{-1}, indicating that C losses from recently established turfgrass cannot be ruled out for future studies.

A funnel plot of $dSOC_{1-10}$ skewed right (Fig. S1), which may indicate publication bias towards high sequestration rates for young turfgrass systems, but also likely reflects sub-group differences, described below. In particular, the funnel plots reflected the systematically lower values found in repeated-measures studies compared to chronosequence studies. Due to the high between-study heterogeneity indicated by I^2, no additional measures were taken to estimate an unbiased mean for $dSOC_{1-10}$.

Mean sequestration rates declined as turfgrass matured (Fig. 2C), to a cross-site mean of 93.5 g C m^{-2} yr^{-1} [63.4; 124] for $dSOC_{30}$, and to 35.4 [−17.9; 88.8] for $dSOC_{50}$. Thus, by 50 years, cross-study mean sequestration rate was not distinguishable from zero. These values are equivalent to CO_2 removal rates of 3.43 Mg CO_2 ha^{-1} $year^{-1}$ [95% CI 2.32; 4.55] at 30 years and 1.30 [95% CI −0.66; 3.26] at 50 years. Funnel plots were balanced for $dSOC_{30}$ and $dSOC_{50}$ (Fig. S1), suggesting no publication bias or structure between subgroup responses.

3.2. Equivalent soil mass accounting

We compared the cross-study mean SOC sequestration rates for 16 studies computed with both FD and ESM accounting approaches. ESM accounting increased mean sequestration rates computed at 10, 30, and 50 years and widened 95% confidence intervals (Fig. 3). The mean increases were largely driven by three datasets, for which ESM accounting greatly increased computed sequestration rates (Fig. S5). However, for most of the datasets, ESM accounting had small impacts on computed sequestration rates, and on a case-by-case basis ESM accounting sometimes increased, sometimes decreased, and sometimes had no impact on computed rates (Fig. S5).

3.3. Meta-analysis of Caruso model

The rise-to-maximum 'Caruso' model did not fit all datasets. Of the 43 datasets that captured multi-decadal dynamics, 28 of them (65 %) converged on a solution when fitted with the Caruso model. Of the datasets that failed to converge, visual inspection indicated that 6 (14 %) had no increase in SOC stocks over time, and 8 (19 %) had a linear increase in SOC stocks through time. The datasets fitted with the Caruso model demonstrated a wide range in the velocity with which they approached steady state (Fig. 4A and B), which is controlled by parameter c (Eq. (1)). The cross-study mean value for c, which represents the sum of SOC input and decay rates, was 0.038 g C m^{-2} yr^{-1} [0.027; 0.0489].

Fitting datasets with the Caruso model in contrast to authors' models did not alter conclusions about SOC sequestration rates during the initial 50 years following turfgrass establishment. The Caruso model predicted higher cross-study mean sequestration rates at 10 years and lower means at 30 and 50 years than authors' models; however, the 95% confidence intervals for both approaches overlapped (Fig. 4C). Our hypothesis that the Caruso model would predict lower sequestration rates for mature turfgrass did not have strong support over the initial 50 years of turfgrass establishment. However, differences between the modeling approaches emerged after 50 years, when many authors' original empirical equations, perhaps dubiously, predicted increases in dSOC/dt (compare Figs. 2B and 4B). Also notable was that cross-study mean $dSOC_{50}$ computed with the Caruso

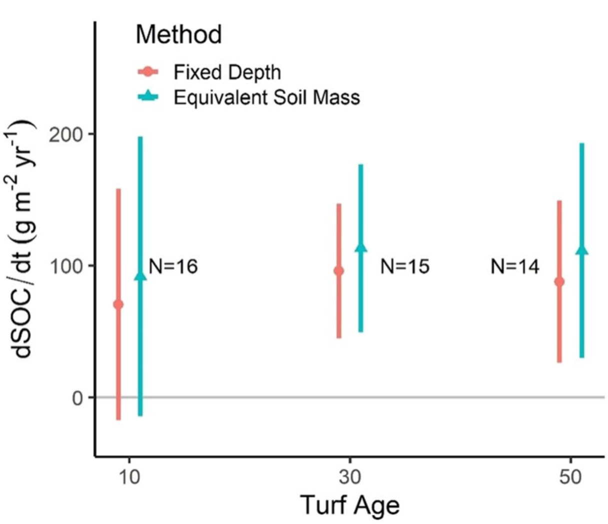

Fig. 3. Cross-study mean and 95% confidence interval for $dSOC_{1-10}$, $dSOC_{30}$, and $dSOC_{50}$, based on fixed depth (FD) or equivalent soil mass (ESM) accounting. All studies originally reported SOC stocks by FD accounting.

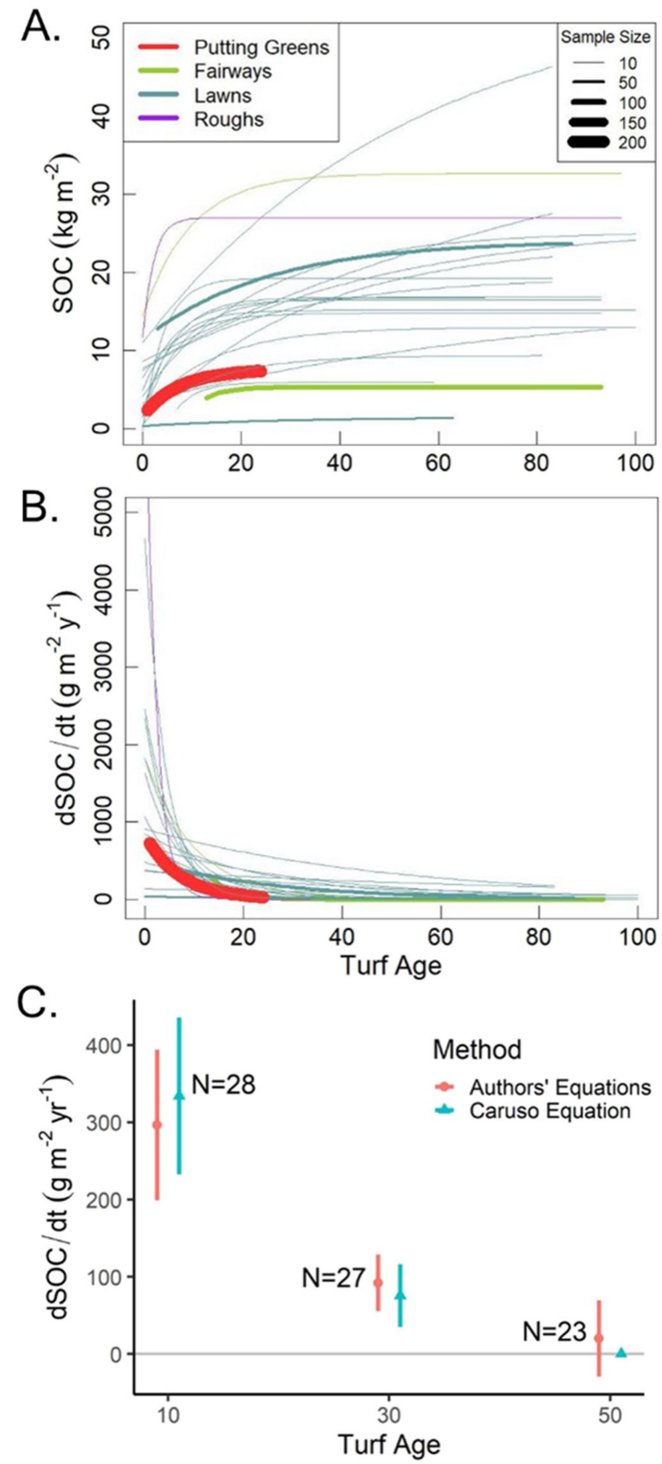

Fig. 4. Re-analysis of chronosequences using an ecological equilibrium (Caruso) model (equation). Note that only 28, or about one-third of datasets, could be fit with the Caruso model. (A) Total SOC stocks versus years since turfgrass establishment. (B) Annual rate of SOC gain or loss, dSOC/dt. (C) Comparison of cross-study mean and 95% confidence intervals using Caruso versus authors' models. Note that the error bars for the Caruso model at t = 50 are too small to be visible.

model had smaller confidence intervals and lower between-study heterogeneity than when computed with the authors' models, due to the fact that the Caruso model predicts dSOC/dt approaches 0 through time in all studies.

Because the confidence intervals for both approaches overlapped during the initial 50 years of turfgrass establishment, and because no solutions for the Caruso model were found for one-third of the datasets, subsequent meta-regressions of $dSOC_{1-10}$, $dSOC_{30}$, and $dSOC_{50}$ were computed only from the authors' original regression models.

3.4. Meta-regression and sub-group analysis

A meta-regression of $dSOC_{1-10}$ versus maximum sampling depth provided no evidence for a relationship between the depth of soil sampled and SOC accumulation rate (Fig. S6). The continental-scale studies of residential lawns by Selhorst and Lal (2013, N = 13 U.S. cities, 15 cm sampling depth) and Trammell et al. (2020, N = 6 U.S. cities, 30 cm sampling depth) showed considerable heterogeneity among locations sampled to a common depth. The heterogeneity attributable to geography far exceeded the heterogeneity that could be attributed to sampling depth. The lack of relationship provided no basis for normalizing $dSOC_{1-10}$ values to a common sampling depth. Therefore, $dSOC_{1-10}$ computed from different maximum sampling depths were pooled for subsequent sub-group analysis.

We evaluated whether the variation in SOC sequestration rates across studies was explained by prior land use, climate region, turfgrass photosynthetic pathway, turfgrass uses, and study methodology. Of these categorical variables, significant differences in $dSOC_{1-10}$ were found among different prior land uses (Q-test $p < 0.01$), turfgrass uses (Q-test $p = 0.02$), and study methodologies (Q-test $p = 0.01$, Fig. 5).

In locations that were previously forested or converted from shrubland vegetation, cross-study mean $dSOC_{1-10}$ was undistinguishable from zero. In contrast, sites converted from other vegetation types or with unknown history had positive values for $dSOC_{1-10}$ (Fig. 5A). Although some previously forested sites did not lose SOC, all sites with $dSOC_{1-10}$ significantly less than zero were previously forested (Fig. S2). The four studies with greatest SOC losses in the short term were all previously forested (Fig. S2, Huyler2017_Auburn_PureLawns −346 g C m^{-2} yr^{-1}; Campbell2014_Roanoke −302 g C m^{-2} yr^{-1}; Raciti2011_Baltimore_FromForests −82 g C m^{-2} yr^{-1}; Wang2014_ForestConversion −52 g C m^{-2} yr^{-1}). When $dSOC_{1-10}$ was evaluated by individual soil layers, several previously forested locations showed losses of SOC throughout the soil profile (Fig. 6). Other vegetation types showed only SOC gains or rates of change not different from zero when evaluated on an individual layer basis.

Köppen climate regions did not have detectable differences in $dSOC_{1-10}$ (Q-test $p = 0.11$). We note that all the previously forested sites that experienced SOC losses were in the humid subtropical Köppen region (Cfa) in the mid-Atlantic and southeastern U.S (Table S1). The potential positive impacts of favorable growing conditions in this region may have been offset by SOC losses due to forest conversion. Similar to climate regions, C3 or C4 photosynthetic pathways did not have detectable differences in $dSOC_{1-10}$.

Turfgrass uses differed in $dSOC_{1-10}$ (Fig. 5B), with lawns and fairways having positive SOC sequestration rates and other turfgrass uses having SOC sequestration rates indistinguishable from zero. Because putting greens and athletic fields are mowed more often, frequently have clippings removed, and therefore accumulate less biomass than less-intensively managed roughs and lawns, a negative relationship between $dSOC_{1-10}$ and management intensity might be expected. However, the small number of datasets for putting greens, athletic fields, and roughs did not allow for robust evaluation of management intensity.

Chronosequences reported a higher average $dSOC_{1-10}$ than repeated measures studies. We note that Qian and Follett (2002) was considered a chronosequence study for this assessment, although it pooled repeated soil testing data over time for golf courses of different ages. This comparison of methods also captured differences in turfgrass age. The repeated-measures studies were all ≤ 4 years in duration, and potentially influenced

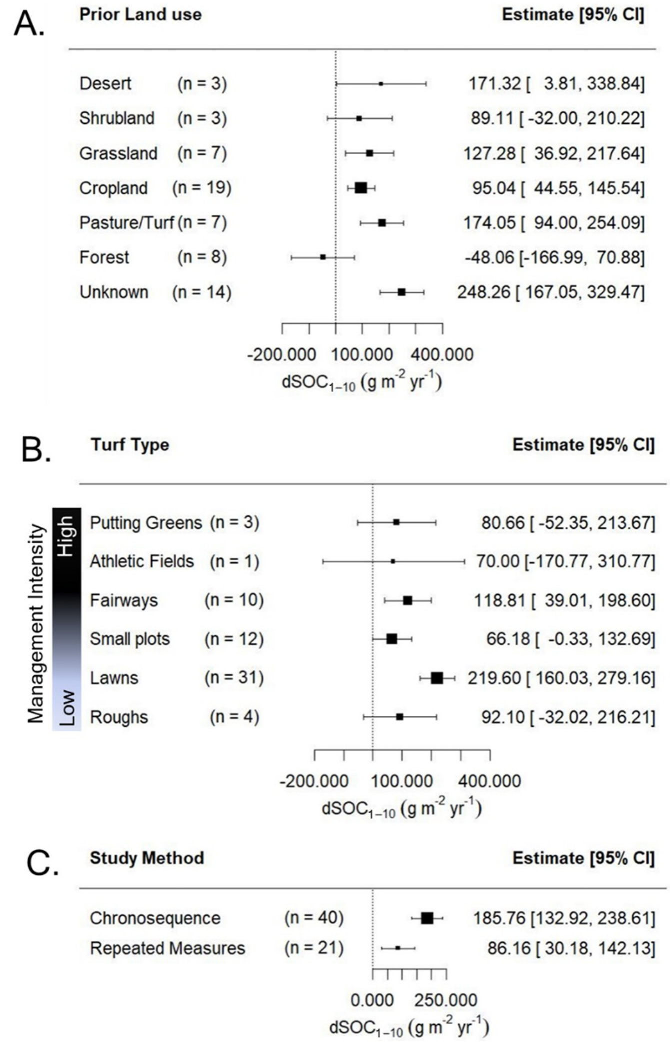

Fig. 5. Group analysis for $dSOC_{1-10}$. SOC changes were computed from authors' regression models, with the exception that equivalent soil mass accounting was used for 16 studies providing sufficient information.

by the disturbance effects of plot establishment, whereas chronosequence studies were assessed at ten years.

While a portion of the between-study heterogeneity could be attributed to prior land use, turfgrass use, and study methodology, a considerable amount of between-study heterogeneity was unexplained. When the three explanatory variables that were individually significant were combined into a single meta-regression model, they explained 69% of between-study heterogeneity in $dSOC_{1-10}$. Residual heterogeneity was still considerable ($\tau^2 = 5641$) and a Q-test for residual heterogeneity was highly significant ($p < 0.01$).

For $dSOC_{30}$ and $dSOC_{50}$, a significant portion of between-study heterogeneity was explained by maximum sampling depth (Figs. S7 and S8). At 30 years, SOC sequestration rate increased by an average of 14 g C m^{-2} yr^{-1} [4; 25] for every 10 cm of additional sampling depth, and sampling depth accounted for 53% of between-study heterogeneity. At 50 years, SOC sequestration rate increased by an average of 24 g C m^{-2} yr^{-1} [2; 45] for every 10 cm of additional sampling depth, and sampling depth accounted for 32% of between-study heterogeneity. When datasets with different sampling depths were pooled, there was not sufficient evidence to support differences in sequestration rate resulting from prior land use, climate, C3/C4 photosynthetic pathway, or turfgrass use at 30 or 50 years. However, when the datasets were adjusted to a common sampling depth of 30 cm, using the coefficients reported above, subgroup analysis of depth-adjusted $dSOC_{30}$ values showed significant differences among Köppen climate regions. The

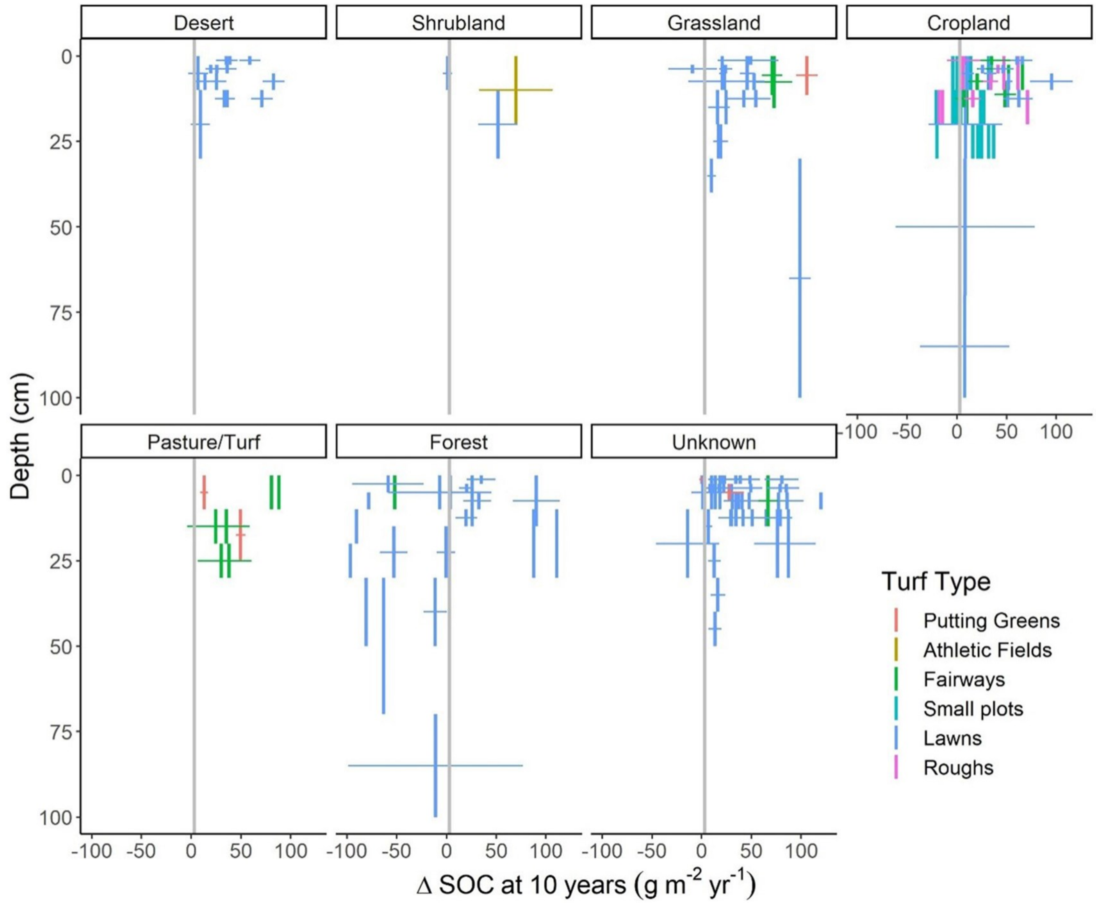

Fig. 6. Depth-discrete $dSOC_{1–10}$, separated by prior land use. Vertical bars indicate the depth range sampled and horizontal bars indicate the standard error of $dSOC_{1–10}$.

region classified as 'humid continental, hot summers' (code Dfa), which encompasses the Midwestern U.S., had significantly greater $dSOC_{30}$ than other climate regions (Q-test p = 0.02). Depth-adjusted $dSOC_{50}$ values did not show differences in sequestration rate at 50 years among subgroups.

3.5. Net greenhouse gas emissions

Estimated mowing events ranged from 14 times per year for lawns in colder climates such as Duluth, Minnesota to 43 times per year for lawns in warm climates such as Los Angeles, California (Table S2). Putting greens were mowed an average of 77 times each year, and fairways an average of 34 times each year. While putting greens and fairways were mowed more frequently than most lawns, ride-on mowers are faster and more efficient than push mowers, and therefore estimated annual mowing emissions were highest for residential lawns, averaging 0.35 Mg CO_2 ha^{-1} $year^{-1}$ compared to 0.25 for putting greens and 0.08 for fairways.

For the N-fertilized scenario, estimated fertilizer requirements based on plant growth potential ranged from 55 kg N ha^{-1} $year^{-1}$ for warm season grasses grown in cooler climates to 327 kg N ha^{-1} $year^{-1}$ for warm season grasses grown in a well-matched climate in Miami, Florida and 344 for cool season grasses grown in Los Angeles, California (Table S2). Emissions associated with synthetic N-fertilizer production ranged from 0.3 to 1.3 Mg CO_2 ha^{-1} $year^{-1}$ to supply turfgrass systems across the climatic gradient, and soil N_2O emissions resulting from fertilizer application had a similar magnitude, accounting for an additional 0.3–1.5 Mg CO_2 ha^{-1} $year^{-1}$ (Fig. 7B). Emissions related to the production and use of N-fertilizer far exceeded mowing-related emissions. On average across all studies, mowing, synthetic N-fertilizer production, and N_2O emissions accounted for 14 %, 41 %, and 46% of total maintenance emissions, respectively (Fig. 7B).

GHG_{net} was highly dependent on assumed N-fertilization rates. In the unfertilized scenario, mowing and N_2O emissions offset 17% of $dSOC_{1–10}$, whereas in the N-fertilized scenario, maintenance emissions offset 32% of $dSOC_{1–10}$ (Fig. 7). Use of synthetic N-fertilizer therefore reduced the strength of emissions removal. However, in both scenarios, cross-study mean GHG_{net} was significantly less than zero (a net sink) for turfgrass aged 30 years or less, and undistinguishable from zero for 50 year-old turfgrass (Fig. 7A). For the N-fertilized scenario, mean GHG_{net} was −3.6 Mg CO_2 ha^{-1} $year^{-1}$ [−5.1; −2.1] over the first decade following establishment, −1.8 [−2.8; −0.8] at 30 years, and − 0.06 [−1.7; 1.6] at 50 years. For the unfertilized scenario, mean GHG_{net} was −4.3 Mg CO_2 ha^{-1} $year^{-1}$ [−5.8; −2.9] over the first decade following establishment, −2.6 [−3.6; −1.6] at 30 years, and − 0.83 [−2.5; 0.87] at 50 years.

4. Discussion

4.1. Key findings and study limitations

The cross-study mean SOC sequestration rate for turfgrass established within the last 10 years (141 g C m^{-2} yr^{-1}) substantially exceeded sequestration rates that have been reported for numerous soil conservation practices, including cropland to grassland conversion (87 g C m^{-2} yr^{-1}, Conant et al., 2017), grazing land fertilization (57 g C m^{-2} yr^{-1}, Conant et al., 2017), cover crop adoption (32 g C m^{-2} yr^{-1}, Poeplau and Don, 2015), and adoption of no-till agriculture (6 to 54 g C m^{-2} yr^{-1}, Ogle et al., 2019). Positive SOC sequestration rates were reported for the major-ity of turfgrass studies reviewed here (Figs. 2 and 6), and net positive sequestration persisted in many cases for 30 years or longer (Fig. 2). These results suggest that turfgrass cultivation may be useful for intentionally building SOC stocks. Our partial GHG budget suggests that turfgrass

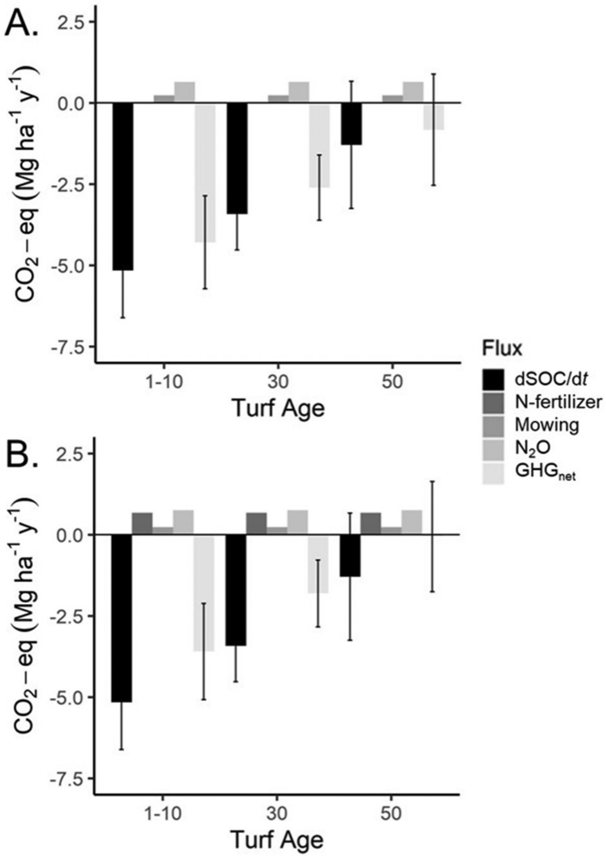

Fig. 7. Component and net greenhouse gas fluxes at 1–10, 30, and 50 years, with negative values indicating atmospheric removal. (A) Unfertilized scenario. (B) Fertilized scenario, with fertilization requirement estimated from a temperature-based growth potential model. For dSOC/dt, the meta-analysis mean and 95% CI interval are shown. No uncertainty analysis was conducted for mowing, fertilizer, and N_2O emissions, and these emissions were held constant through time. For GHG_{net}, meta-analysis mean and 95% CI were computed using the standard error of dSOC/dt as a weighting factor.

maintenance practices partially, but not completely, offset SOC sequestration over the first 30 years following turfgrass establishment. Even in a high-intensity management scenario that assumed water sufficiency and N-fertilization rates to match growth potential, we estimated that turfgrass systems, on average, do not reach a compensation point between emissions and sequestration until approximately 50 years following establishment.

Human modification of soils through intensive production is often described in terms of its degrading impacts that result in SOC losses, and less often as a process that can drive SOC accumulation. However, elevated levels of SOC due to landscaping are commonly described in urban settings in the U.S. compared to native soils (Golubiewski, 2006; Trammell et al., 2020). Modified, landscaped soils can be viewed as a contemporary extension of anthropogenic or "cultural" soil layers enriched in SOC that resulted from ancient settlements, for instance in urban settlements in Russia (Vasenev and Kuzyakov, 2018), China (He and Zhang, 2009), and from plaggen farming practices in Northern Europe (Blume and Leinweber, 2004). Through additions of organic materials and intentional cultivation, humans have historically built lasting reservoirs of SOC in some settings. However, such intensification of SOC content requires inputs of nutrients and other resources, and the accumulation of SOC content alone does not describe the net climate impact of intensification practices. In the case of turfgrass cultivation, estimated GHG_{net} suggests that turfgrass cultivation may be a negative emissions practice (i.e., C sink) for at least 30 years when moderate N fertilizer rates matching plant demand are used.

However, this meta-analysis was unable to address questions about how maintenance practices impact carbon sequestration. Few datasets were available for high-input maintenance systems (i.e., athletic fields and putting greens), and limited information was provided on the maintenance practices used in the chronosequence studies, making it difficult to quantitatively evaluate the GHG impacts of management intensity. An accompanying review paper (Wang et al., 2022) discusses findings from individual studies on the SOC and GHG impacts of turfgrass maintenance practices. For instance, Qian et al. (2003) estimated from model simulations that returning mowing clippings could increase SOC sequestration by 28 to 59 %. Increasing the amount of plant material returned to soil is therefore expected to increase SOC sequestration rates, although it could not be supported across multiple studies by this meta-analysis.

Another limitation of this study is that we did not address the water requirements of turfgrass, which is a major environmental concern, particularly in semi-arid and arid parts of the U.S. For instance, the State of California has set a goal of removing 4600 ha^{-1} of ornamental turfgrass between 2022 and 2030 (CNRA, 2022). Although many U.S. municipalities have increased water conservation through time (Gonzales and Ajami, 2017; Huntra and Keener, 2017; Sullivan et al., 2017), and turfgrass research has long focused on improving turf drought performance (Braun et al., 2022), the high water demands of turfgrass still challenge available water resources (Cabrera et al., 2013; Kjelgren et al., 2000). Even in non-arid regions of the U.S., supplemental irrigation is often applied to turfgrass. For instance, Kjelgren et al. (2000) estimated that 9–13% of municipal water use was used for landscaping in Atlanta, Georgia and Washington, D.C., two U.S. cities that are in humid subtropical Köppen climate zones and receive summer rainfall. Groffman et al. (2016) showed that 85% of survey respondents in Miami, Florida (tropical monsoon Köppen climate zone) reported irrigating their lawns, similar to the 89% percent of households in Phoenix, Arizona (subtropical desert Köppen climate zone). The potential carbon sequestration benefits of turfgrass therefore comes at the expense of consuming irrigation water.

Irrigation can also have a considerable carbon footprint, and a complete GHG budget would need to include irrigation-related emissions. We felt a robust accounting of irrigation-related emissions was not possible at the nationwide scale of this study, because the extraction, conveyance, and treatment of irrigation water and the energy density of electricity are regionally specific. However, several past case studies have provided estimates of irrigated-related emissions. Braun and Bremer (2019) estimated irrigation pumping was responsible for 0.11–0.15 Mg CO_2 ha^{-1} yr^{-1} for a trial in Kansas, U.S., accounting for 6.7% to 8.3% of total maintenance emissions. Tidåker et al. (2017) estimated irrigation pumping accounted for 1% of maintenance emissions on two Swedish golf courses. Townsend-Small and Czimczik (2010) employed a 10× higher estimate for the emissions intensity of irrigation pumping (1.93 Mg CO_2 ha^{-1} yr^{-1}) based on Schlesinger (1999). They estimated that in Southern California, U.S., irrigation accounted for 24–48% of total maintenance emissions, depending on fertilization rates. This higher estimate for irrigation-related emissions would equate to 36% of mean $dSOC_{1-10}$ and 56% of mean $dSOC_{30}$ computed here, and would considerably reduce the potential climate benefits of turfgrass. More research on irrigation-related emissions is urgently needed to improve sustainability assessments.

4.2. Comparisons of GHG_{net} with earlier studies

Earlier efforts to compute net emissions from turfgrass systems similarly concluded that residential lawns (Selhorst and Lal, 2013; Townsend-Small and Czimczik, 2010) and golf courses (Selhorst and Lal, 2011) were net CO_2 sinks when low to moderate rates of N-fertilizer were applied, even after accounting for the hidden carbon costs of maintenance. Tidåker et al. (2017) concluded that golf course roughs in Sweden, but not fairways, were net CO_2 sinks. However, a major factor influencing the strength of the estimated CO_2 sink in different studies is the handling of N emissions. A major difference between our calculations and those by Selhorst and Lal (2011, 2013) is that we included N_2O emissions. N_2O was a large source that exceeded mowing emissions in our calculations, even in the unfertilized scenario. In our N-fertilized scenario, we also computed N-fertilization rates 4–5 times greater than the rates Selhorst and Lal (2013) assumed were used on residential lawns. However, our rates were less than half of the 'high' fertilization rates they reported were used by commercial lawn care companies. On the other hand, we used a lower emissions factor for CO_2 associated with N-fertilizer production (3.78 kg CO_2 kg^{-1} N versus 4.77). Based on discussions with turfgrass professionals, we assumed urea (46–0–0) is the main form of N-fertilizer used in turfgrass systems, which has a substantially lower emissions factor than formulations containing ammounium nitrate (Haxha and Christensen, 2018). We also assumed greater mower efficiencies and computed lower mower emissions than Selhorst and Lal (2013).

Townsend-Small and Czimczik (2010) evaluated emissions associated with a low N-fertilizer regime (100 kg N ha^{-1} yr^{-1}) and a high N-fertilizer regime (750 kg N ha^{-1} yr^{-1}) and found that lawns were only a net sink at the lower N-rate. Using a similar accounting approach as we did, they determined that emissions associated with fertilizer production and N_2O exceeded turfgrass CO_2 removal at the high N-rate. Their high N-fertilizer rate was considerably higher than N rates we produced in our scenarios, which may reflect a trend towards lower recommended fertilization rates through time (Gelernter et al., 2016). However, they similarly concluded that turfgrass emissions are highly dependent on N-fertilization rates.

The emissions associated with N-fertilization are a major source of uncertainty in assessing the net climate impact of turfgrass. N-fertilization rates were unknown for the chronosequence studies described here. Estimating N-fertilizer rates for residential lawns is difficult because recommended rates can vary by a factor of 6 or more (Townsend-Small and Czimczik, 2010), actual application rates among homeowners and lawncare professionals are highly variable (Campbell et al., 2014; Selhorst and Lal, 2013), and fertilization practices do not correspond with soil N supply (Groffman et al., 2016). Methods for estimating the impacts of fertilizer on N_2O production are also imprecise (Braun and Bremer, 2018; Van Groenigen et al., 2010). Here we applied the IPCC protocol for estimating N_2O production as 1% of fertilizer-N applied (IPCC, 2019). However, Braun and Bremer (2018) estimated the mean emissions factor from a review of 14 turfgrass datasets to be 1.9 %. When we apply that higher emissions factor in our calculations, we estimate the additional N_2O emissions would increase GHG_{net} by 1.5 Mg CO_2 ha^{-1} yr^{-1}. However, the review by Braun and Bremer (2018) also demonstrated that very few studies have quantified N_2O emissions from turfgrass systems, and that a linear relationship between fertilizer rates and N_2O production cannot be assumed.

In addition to the uncertainties related to predicting N-fertilizer related emissions, a limitation of the GHG_{net} calculations was that we did not account for lower plant growth rates that would be expected in an unfertilized versus an N-fertilized scenario. Such a reduction in plant growth might also reduce SOC accumulation rates. Braun and Bremer (2019) tested the impacts of high- and low-input management regimes on zoysiagrass (Zyosia spp.) turf, following plots for 3 years from establishment. They found similar SOC accumulation rates between high-input treatments that received urea fertilizer and medium irrigation, and low-input treatments that were unfertilized and received low irrigation. However, because low-input turfgrass required less frequent mowing and had lower fertilizer-related emissions, it had lower maintenance emissions, and thus lower GHG_{net} than high-input turf. Their study showed that less intensively managed turfgrass has lower net emissions, despite having lower plant production. This is the only study, to our knowledge, that has evaluated the net GHG impacts of maintenance intensity, and more research on other turfgrass species and in other climates would be useful.

4.3. Does SOC accumulation level-off?

The decline in mean dSOC/dt to zero over the first 50 years after turfgrass establishment was a key result from this meta-analysis (Fig. 2). This result was not altered depending on whether data were fitted by polynomial regression or the Caruso model (Fig. 4C). However, sequestration rates after 50 years would be influenced by the model choice. Applying a rise-to-maximum model to describe long-term trends in SOC is supported by ample data from large numbers of long-term studies from agricultural (Caruso et al., 2018; Poulton et al., 2018) and natural systems (Lajtha et al., 2018). In turfgrass systems, Shi et al. (2012) showed an increase in soil microbial abundance and enzymatic activity across a turfgrass chronosequence, suggesting increased SOC decomposition through time and microbial regulation of soil C accumulation. Such data suggest that increases in dSOC/dt after many decades of consistent management are unlikely, and therefore that applying polynomial regressions to fit SOC(t) relationships will give misleading representations of dSOC/dt dynamics.

It is also clear, however, that linear relationships provided the best description of SOC accumulation in several locations, including: residential lawns spanning over 100 years in Massachusetts (Trammell et al., 2020), Maryland (Raciti et al., 2011; Trammell et al., 2020), and New Hampshire (Contosta et al., 2020), lawns spanning 100 years in Salt Lake City, Utah (Smith et al., 2018), lawns spanning 81 years in Los Angeles, California (Townsend-Small and Czimczik, 2010; Trammell et al., 2020), and golf course fairways spanning 34 years in Saratoga, Wyoming (Qian and Follett, 2002). These studies suggest turfgrass can maintain high rates of SOC accumulation without apparent decline for multiple decades in some settings.

Overall, individual studies demonstrated considerable variation in the trajectory of SOC sequestration rates. This variation is not surprising, given that studies varied considerably in their starting SOC content (Fig. 2A), which may indicate differences in soil carbon deficit and their ability to accumulate further stocks (Stewart et al., 2007). Studies also varied in climate and soil mineralogy, which have major influences on decomposition rates (Rasmussen et al., 2018). Decomposition rates, in combination with plant C input rates, control the velocity with which SOC stocks approach an ecological equilibrium. The fact that no leveling-off was detected in some turfgrass chronosequences may be because they did not cover a long enough period to reveal non-linear dynamics. The inherent imprecision of chronosequence studies is also relevant. The small sample sizes of many of the chronosequences, potential differences in management and environmental setting among turfgrass of different ages, and the inherent high variability of SOC stocks (Kravchenko and Robertson, 2011) all add uncertainty to model fitting and interpretation of SOC dynamics.

4.4. The beginning and end of turfgrass lifespans

Because turfgrass establishment often accompanies land use change, it is important to consider the emissions stemming from conversion from prior vegetation types. The meta-analysis showed net accumulation of SOC following establishment in most settings, but several datasets documented SOC losses following forest to turfgrass conversion (Figs. 5 & 6, Campbell et al., 2014; Huyler et al., 2014; Raciti et al., 2011). These forest conversion datasets provide a cautionary example of how turfgrass cannot immediately compensate for the C losses associated with land development in all environmental settings. Raciti et al. (2011) reported that it took 20 years following turfgrass establishment to regain near-surface SOC stocks to the levels measured in urban forests. Forest removal also has legacy impacts on deep SOC losses that are slow to regain even after many decades (Billings et al., 2018). Since forests contain much C in aboveground biomass, the emissions from land use conversion are also considerably greater when accounting for whole-ecosystem C changes.

It is also instructive to consider the end-point of a turfgrass system, and its eventual replacement with other land uses. As evidenced by the many long-term chronosequences presented here, turfgrass is a perennial system that can remain in place for many decades, with renovation events sometimes employed to improve growth and aesthetics (e.g. reseeding, aeration, dethatching). However, ornamental turfgrass is presently being removed in several Western U.S. cities over water concerns (Cowan, 2022). Additionally, as SOC accumulation slows in maturing turfgrass and mowing- and fertilizer-related emissions continue, turfgrass systems will inevitably shift from being GHG sinks, or net neutral, to being GHG sources. How should turfgrass be managed at that time to minimize emissions? How can the sequestered SOC be protected, to not re-release it back to the atmosphere? Re-releasing temporarily stored CO_2 into an atmosphere with higher CO_2 reservoirs can potentially worsen climate change, as biological sink capacity is diminished (Kirschbaum, 2006).

One option for addressing this transition from net C sink to net source is to delay reaching this point for as long as possible, by minimizing maintenance emissions. Electric mowers are increasingly available and have been estimated to reduce CO_2 emissions by 49.9% and 32.3 %, respectively, for push and riding mowers over their lifecycles (Saidani and Kim, 2021). Using locally available organic materials as N-fertilizer sources, such as compost and biosolids, avoids the emissions associated with synthetic N-fertilizer production, and when properly managed can reduce secondary GHG emissions from excess nitrogen in the environment (Zhao et al., 2020). In our analysis, production of urea-based fertilizers accounted for 41% of the total maintenance emissions associated with turfgrass management (Fig. 7B). Using a locally-available organic N source could therefore, theoretically, reduce turfgrass management emissions by a substantial level. As mentioned previously, the study by Braun and Bremer (2019), also suggested the low-input turfgrass can be an approach to reduce GHG_{net}, despite slower plant growth. If turfgrass can be maintained and its period of zero or low net emissions can be extended, this may be preferable from a GHG perspective than transitioning turfgrass to other land uses, because of the potential for SOC losses upon removal of turfgrass.

A second option for addressing the transition from net carbon sink to net source could be to incorporate woody biomass into landscaping—turfgrass with trees and shrubs—to further increase C accumulation beyond what can be accomplished by pure lawn. For instance, Huyler et al. (2017) showed lawns with turfgrass and trees had higher C stocks, and reached maximum C stocks more quickly, than pure lawns in Alabama, U.S.. Woody biomass develops deeper and more persistent roots than non-woody biomass, where it can develop into more persistent SOC stocks (Dijkstra et al., 2021). In addition, woody biomass stores substantial C aboveground, and where water availability is sufficient, trees help to build higher urban C stocks than can be stored in soil alone (Contosta et al., 2020; Golubiewski, 2006).

In situations where turfgrass needs to be replaced with other vegetation or land uses, applying reduced-tillage principles to replace turfgrass rather than mechanically removing may help to retain SOC stocks. Herbicide application, solarization, or sheet mulching are non-mechanical techniques to kill turfgrass and prepare it for other plantings. In smaller areas, sheet mulching with organic materials such as cardboard and compost is a common way of employing locally available waste materials to simultaneously smother grass and build a thick layer of organic material, which new plants are placed into (Barber et al., 2019). Although gradual SOC losses can be expected if plant productivity is reduced, burying SOC reduces its decomposition rate (Kirschbaum et al., 2021; Van Oost et al., 2007).

5. Conclusions

Urbanizing landscapes are believed to be significant contributors to climate change (Huang et al., 2019; Ürge-Vorsatz et al., 2018), due in part to being a concentrated source of GHG emissions (Moran et al., 2018). This meta-analysis suggests that turfed landscapes may provide temporary GHG reductions in urbanizing landscapes through high SOC sequestration rates. Cross-study mean SOC sequestration rates for turfgrass ≤ 10 years post-establishment exceeded sequestration rates reported for a range of other soil conservation practices. However, SOC sequestration rates also declined to zero over the initial 50 years following turfgrass establishment. Estimated net GHG emissions were highly dependent on N-fertilization practices. However, even with N-fertilizer applied at a rate suggested by a temperature-based growth potential model, turfgrass systems were estimated to be a net CO_2 sink on average, after accounting for mowing, fertilizer, and N_2O emissions. There is some experimental evidence suggesting that N-fertilization is not necessary to achieve net SOC sequestration in turf; however, additional research is needed to fully evaluate this. Irrigation-related emissions were not estimated due to lack of data, and these emissions, as well as the high water demands of turfgrass, need to be addressed in arid and semi-arid regions. Additionally, the datasets analyzed here consisted mostly of C3, 'cool-season' grasses in the U.S. Future research will need to address whether these findings hold for sub-tropical and tropical regions.

Realizing the full negative emissions potential of turfgrass requires attention to its entire life cycle, including establishing turfgrass in locations that are not vulnerable to large C losses, continuously managing turfgrass to minimize mowing and fertilizer-related emissions, and avoiding re-emission of stored SOC when mature turfgrass is transitioned into other uses. When turfgrass is removed, as is presently occurring in some drought-impacted regions of the U.S., employing non-mechanical methods of turfgrass removal should help to conserve previously-accumulated SOC stocks.

CRediT authorship contribution statement

Claire L. Phillips: Conceptualization, Methodology, Formal analysis, Data curation, Writing – original draft, Funding acquisition. Ruying Wang: Conceptualization, Investigation, Data curation, Writing – review & editing. Clint Mattox: Writing – review & editing. Tara L.E. Trammell: Resources, Writing – review & editing. Joseph Young: Resources, Writing – review & editing. Alec Kowalewski: Writing – review & editing, Project administration, Funding acquisition.

Data availability

Data and R code used to conduct the analysis and create figures are available through the Ag Data Commons. https://data.nal.usda.gov/dataset/turfgrass-soil-carbon-changes-through-time-v1.

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.2022.159974.

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