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Exploring the role of urban nature in mitigating the climate footprint of urbanization in Ethiopia

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ABSTRACT

Urban centers in sub-Saharan Africa face climate vulnerabilities due to rapid urbanization and outdated development strategies that prioritize grey infrastructure over natural elements. In Ethiopia, urban green spaces remain underutilized despite their potential to enhance climate resilience. This study aims to explore the climate mitigation potential of green spaces in Hawassa, Ethiopia, by assessing carbon storage in trees using allometric equations within a customized i-Tree Eco model, complemented by soil and litter carbon analysis for selected parks. We collected data from stratified random sample plots across land uses, along with climate and location information to parameterize the model. Urban trees, soil, and litter carbon pools together stored 78,199 tC, mitigating 286,990.30 tCO_2e, with carbon sequestration offsetting 4.9 % of the city's annual emissions. The highest carbon stock was observed in soil (189.8 ± 8.5 tC ha¯1), while litter carbon was the least (1.08 ± 0.12 tC ha¯1). Hawassa's tree carbon density (12.01 tC ha¯1) was lower than other Ethiopian cities, influenced by urbanization and methodological variations. In Hawassa, land uses with minimal impervious and greater green space exhibited the highest carbon storage. Carbon sink positively correlated with tree metrics, while urbanization had a negative effect. Spatial mappings revealed an uneven distribution of carbon stocks, with impervious areas dominating low-carbon storage regions. These findings highlight the role of green spaces in climate mitigation and the need to integrate them into spatial planning and carbon policies. Ethiopian cities must balance grey and natural elements to enhance climate resilience and achieve emissions self-sufficiency.

Introduction

Anthropogenic driven climate change is increasingly impacting the Earth's systems, manifesting in rising global temperatures, shifting precipitation patterns, and warming oceans, with far-reaching consequences that will continue to shape the future [13]. One major driver of these changes is the increase in global greenhouse gas (GHG) emissions, which reached 53.8 Gt CO_2e in 2022 [6]. Carbon dioxide (CO_2) and methane (CH_4) are dominant GHGs and primarily originate from fossil fuel combustion and waste decomposition, respectively [30].

Urban areas are increasingly vulnerable to climate change, with expected temperature increases of 1.3–3.0 °C, precipitation changes ranging from −9% to +15 %, and sea level rise of up to 60 cm by the 2050 s [44]. Cities consume 60–80 % of global energy and contribute to 72 % of GHG emissions [54], making them warmer than surrounding rural areas due to the urban heat island effect. These climate risks are particularly pronounced in cities of the Global South, where rapid and often unplanned urbanization exacerbates existing vulnerabilities. In Africa, many urban centers risk adopting a 'pollute now, clean up later' development strategy, prioritizing short-term economic growth over environmental sustainability [58]. With urban population growth outpacing other regions, Africa is projected to add over 950 million people to its urban population in the next three decades [2]. Sub-Saharan Africa, the fastest urbanizing region, is expected to reach 50 % urbanization by 2030 [51]. The proportion of the population living in this region of Africa has already increased from 22 % in 1980 to 40 % today [2]. As a result, urban centers in this region are among the most vulnerable to climate change risks, necessitating urgent mitigation and adaptation strategies.

Ethiopia has implemented climate resilience strategies to counteract rising emissions. According to the Ethiopia's Ministry of Planning and Development (EMPD), emissions have increased from 108,333 $GgCO_2e$ to 350,843.9 $GgCO_2e$, while removals grew from 60,774.2 $GgCO_2e$ to 108,422 $GgCO_2e$ between 1994 and 2018 (EMPD, 2022). Although the

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country's per capita emission in 2022 was just 1.63 t CO_2e [6], projections indicate it could reach 403.5 million t CO_2e by 2030 [8]. To mitigate this, Ethiopia's Climate Resilient Green Economy initiative targets a 64 % emission reduction by 2030, with urban green spaces playing a key role [32]. This notion is also highlighted in the African Union Green Action Recovery Plan of 2021–2027 [2], which supports the Sustainable Development Goal 11 that focuses on universal access to urban green spaces by 2030. However, urban development strategies frequently overlook nature-based solutions (NbS) for climate resilience [51].

Urban nature, including wild habitats and manmade green spaces (e.g., designed parks), enhances urban resilience by reducing atmospheric carbon through photosynthesis and acting as carbon sinks. These NbS absorb atmospheric CO_2 through photosynthesis and store it as biomass [2]. Globally, urban green spaces stored 7.4 billion tons of carbon (C) and sequestered 217 million t C every year [27], making them vital components of urban climate strategies. Studies in the Global North have long emphasized urban green spaces as important C reservoirs and integrated them into urban climate strategies [3,31,40]. For instance, Gill et al. [13] showed that a 10 % increase in urban green spaces cover in high-density areas of Manchester, UK could offset temperature rises, while a 10 % reduction could raise temperatures by up to 4 °C. These studies highlight that neglecting urban green spaces increases urban communities' climate vulnerability.

Despite their importance, carbon accounting for urban green spaces in Ethiopia is limited, with only a few studies focusing on specific urban green spaces types. Woldegerima et al., [59] reported that Addis Ababa's urban green belt stored 552,415 t C, but their analysis excluded inner-city parks and neighborhood greenspaces. Muluneh and Worku [33] found a mean aboveground carbon storage of 745.17 t C ha^{-1} in Dessie city, while Feyisa et al. [9] estimated 82.13 t C ha^{-1} for selected urban green spaces in Hawassa. However, these studies did not account for C loss from dead trees, even though long-term CO_2 dynamics change as trees grow [36]. Although previous studies have already assessed soil organic carbon (SOC) across various types of urban green spaces in Hawassa [9], urban parks remained unstudied in this context. Therefore, this study specifically focuses on urban parks to fill that data gap and complement earlier work. By doing so, we build a more comprehensive understanding of soil carbon storage across all major green space categories in the city.

Most of urban green spaces in the Sub-Saharan Africa, including Ethiopia contribution to climate change mitigation and alignment with national strategies remains uncertain, leading to an underestimation of their C storage potential and their exclusion from urban planning. Using Hawassa as a case study, we aim to fill this gap by evaluating the contributions of urban green spaces in offsetting GHG emission. We hypothesized that C storage varies with tree metrics, with greater influence in areas with higher canopy cover and lower urbanization levels. The objectives are to: 1) quantify C sequestration, total storage, and C release by the urban trees within the city boundaries; 2) estimate C storage in dead litter and urban soils, focusing on undisturbed, forest-like urban parks; and 3) evaluate the CO_2 offsetting efficiency of urban green space types in various locations. By integrating carbon data into urban planning frameworks, this research provides actionable insights to enhance climate resilience in rapidly urbanizing Sub-Saharan Africa cities like Hawassa.

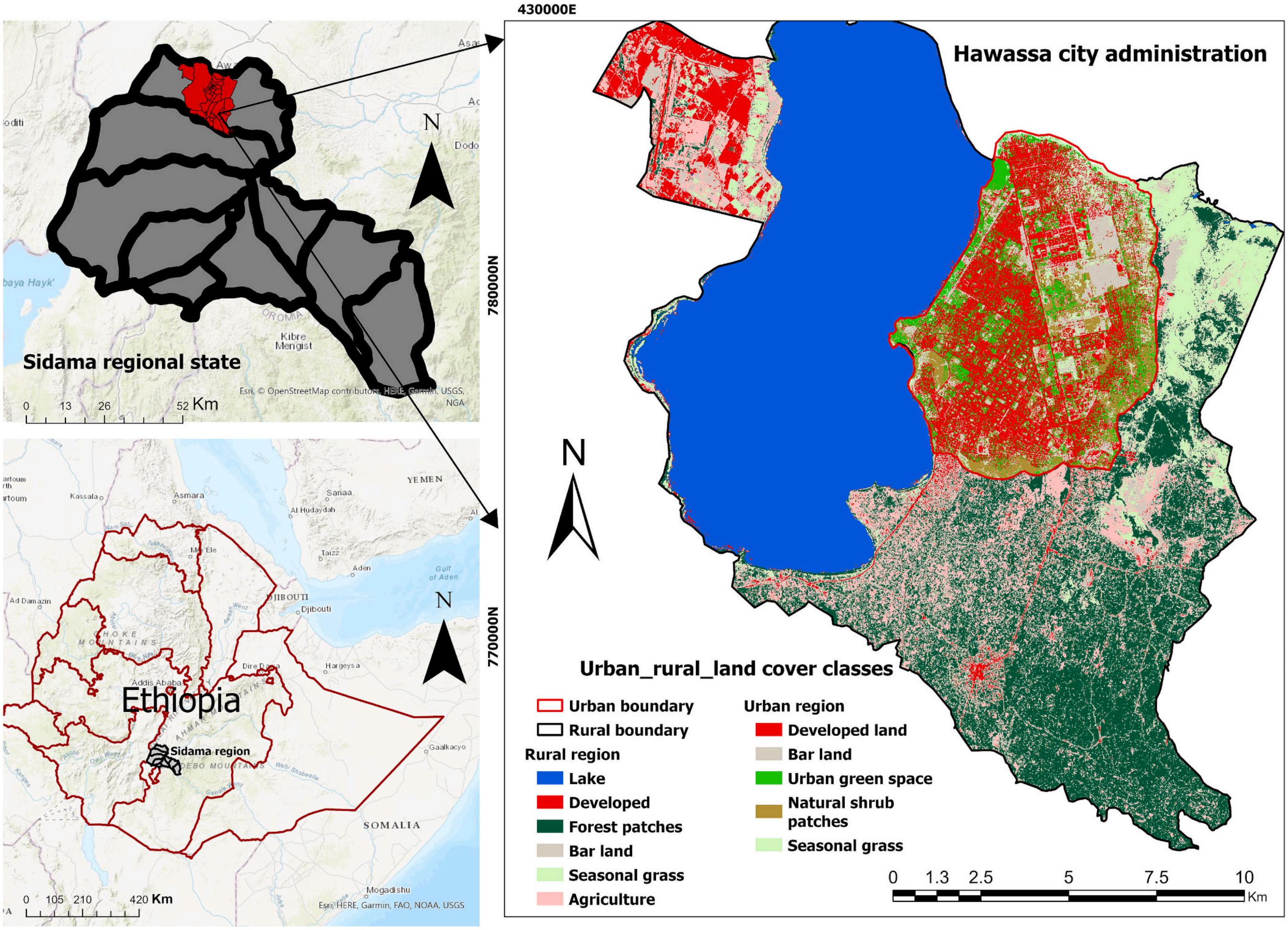

Fig. 1. Location and land cover classification map of the study area showing both the planned development boundary and the administrative boundary.

Methods and Materials

Study area

Hawassa is a medium-sized regional city in southern Ethiopia, located along the Addis Ababa–Moyale (Kenya) highway, 275 km south of Addis Ababa. It is situated in the central Rift Valley, with a geographical location between 6°45′00″ to 7°05′00″ latitude and 38°25′00″ to 38°30′46″ longitude (Fig. 1). The city spans an elevation range from 1680 to 1930 m above sea level and covers 157.2 km2 administrative area [16].

Hawassa has two major spatial extents: an administrative boundary that includes both rural and urban districts, and a planning boundary that serves as the focus area of this study (Fig. 1). As one of Ethiopia's rapidly growing secondary cities, the total population of the city administration was recorded at 371,826 in 2016, based on projections from the 1999 census [16]. The population growth of the urban region, with an estimated growth rate of 4.8 %, is driven by population increase and economic activities [46].

The city is characterized by bimodal rainy seasons and is classified within the subtropical highland agro-ecological zone. The main rainy season occurs from June to September and a shorter one from March to May—along with a dry season from October to February. Hawassa receives an average annual rainfall of 956 to 1,013 mm, with the highest intensity of rainfall in July and August [62]. Hawassa City's average temperatures range from 10 °C to 31.5 °C, with extremes from 6 °C during the cool season (mid-June to early October) to 34 °C during the hot season (February to May), while maximum evapotranspiration reaches 1255 mm [50].

According to a recent report of the city administration, Hawassa boasts two city parks, 140 recreational greenery lots, and 4,740 indigenous trees [5]. These enclosed urban parks are established along the shores of Lake Hawassa and are considered the 'lungs of the city' by local residents. The other common urban green space types are institutional forests, amenity green spaces, private gardens, neighborhood green spaces, street trees, green belts, and lakeside green spaces (Table 1).

Conceptual foundations of the study

The spatial variation of carbon (C) storage in urban areas is influenced by urban morphological types and land cover composition, which shape the extent to which ecosystem services (ES) are delivered and thus contribute to climate change mitigation [13]. This aligns with resilience theory [55], which provides the theoretical foundation for this study, considering cities as dynamic socio-ecological systems [1]. This theory highlights three key dimensions: (1) it identifies critical drivers—such as the balance between pervious and impervious surface covers—that intensify climate change impacts; (2) it recognizes threshold levels of imperviousness beyond which the capacity of urban areas to provide ES declines; and (3) it emphasizes resilience-building strategies, particularly the integration of nature-based solutions (NbS), such as urban green infrastructure, into the built environment. This informs the study's focus on assessing how spatial configurations of green spaces affect C storage and other ES delivery in urban landscapes.

To operationalize the central ideas of this research, several key ecological variables were considered: tree species, diameter at breast height (DBH), tree canopy cover (TCC), leaf area (LA), and health condition of urban trees. These variables were analyzed in relation to three major carbon-related outcomes: carbon storage, carbon sequestration, and carbon loss. Carbon storage represents the long-term accumulation of carbon within urban vegetation, primarily in tree biomass and soil, while carbon sequestration refers to the annual uptake of atmospheric CO_2 by vegetation through photosynthesis [25]. However, it is important to note that while young trees continuously absorb CO_2 as they grow, the stored carbon is gradually released back into the atmosphere once they die and decompose [47]. The inclusion of tree health condition adds an important dimension, as it influences both the carbon retention capacity and potential carbon loss due to tree mortality. This helps to understand how urban green infrastructure can mitigate the climate footprint of cities by enhancing ecological performance and carbon dynamics. We employed i-Tree Eco model (Eco Model) to estimate these carbon variables, which is one of the widely used tools beyond its original application context (e.g. [11,25].

Table 1

Stratification of the study area by clustering similar urban green spaces types across various Urban Morphological Types, including descriptions of each cluster and the number of randomly allocated sample plots for each stratum.

Green space clusters	Abbreviation	Description	Area (ha)	Allocated plots
Green spaces in public facilities	PFS	Green spaces in hospitals, educational centers, and other institutions	723	24
Recreational green areas	RGA	Urban parks, amenity green spaces along lakeside and neighborhoods	195	26
Green spaces in settlement areas	GSS	Residential green areas and private gardens	1975	40
Business district green spaces	BDS	Green spaces in highly developed areas such as the commercial, industrial, and other business zones	678	29
Street and road trees	STS	Green highways, bus stops, and all streets including residential roads	960	35
Green spaces in vacant urban land	VUL	Unutilized land with fragmented inner city shrub patches and public open areas including plaza	203	23
Unmaintained green area	UGS	Natural areas out of the management of the city administration	298	20
Undeveloped green areas	UGA	Inner city open space designated for a particular green area (e.g. urban agriculture) but not well-developed	166	20

Eco model calibration and parameterization

The Eco model, formerly known as UFORE model, was initially developed by the United State Department of Agriculture (USDA) Forest Service to analyze the structure and functions of urban forests in cities across the United States [19]. The model consists of five distinct components, of which two of them are useful to analysis the variables in this study (Fig. 2). Module A inputs field-collected data to assess vegetation structure, while Module C estimates carbon storage and sequestration using allometric equations, tree growth, mortality, and decomposition [39].

The application of this model to assess the ES of urban forests in most African cities remains limited and less understood. However, its applicability in Ethiopia was validated and implemented for the first time to investigate various ES provided by urban forests of two cities, namely Adama [26]and Hawassa [11]. Using the model beyond its original climate context requires extensive data inputs, careful calibration, and adapts to the unique climate, location, and vegetation of the study areas [61]. Accordingly, we modified both the Eco model and its database by incorporating local information (Fig. 3). The database was calibrated by

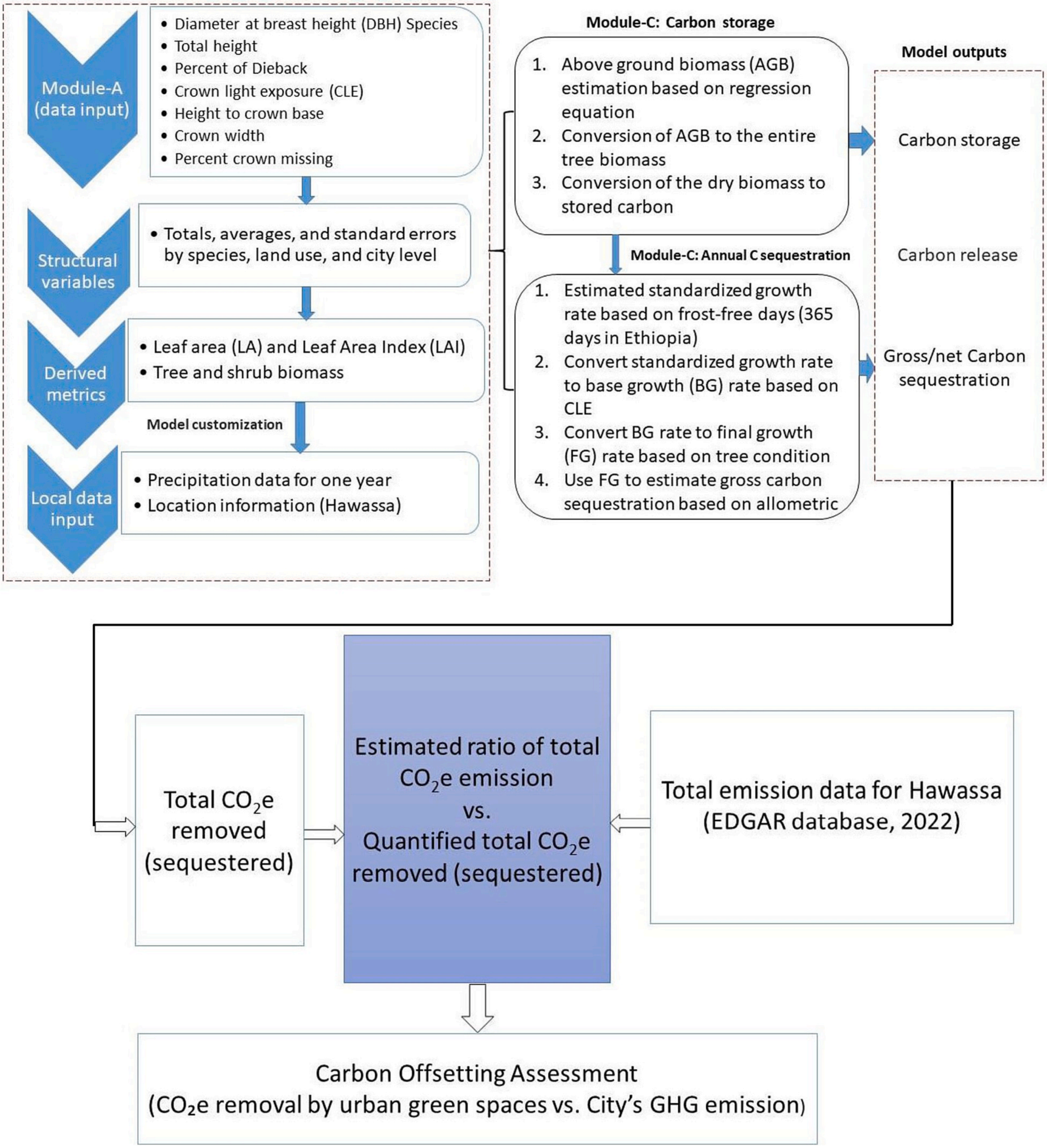

Fig. 2. Conceptual framework for assessing carbon metrics using the i-Tree Eco model and evaluating the offsetting potential of urban green spaces by comparing annual carbon sequestration with the total annual emissions of Hawassa City.

manually adding geographical information, one year of recorded pollution and rainfall data, and other local climate information of Hawassa. We further configured the model by importing geospatial land use data, location information, and specific climate characteristics of the city [38]. We obtained input data, including pollutant and precipitation data from the Ethiopian Federal Meteorological Agency, as well as land use Esri shapefile (geospatial layer) from Hawassa City administration.

The database recognizes only 6500 tree species, and we found that many of Ethiopia's native species were missing. To address this, we identified and added these missing species along with their growth characteristics and ecological traits. This process was guided by the reference book Useful Trees of Ethiopia [4], and validated with the support of local forestry experts. To better reflect the local climate of the study area, we adjusted the default frost-free period to 365 days, given that Ethiopia experiences no frost throughout the year. In the Eco model, the allometric equation type was switched to a tropical variant, selected from the model's library of approximately 150 equations covering both tropical and non-tropical species [28].

Land use classification

Land surface cover was classified into built-up areas, barren land, manmade green spaces, and natural shrub patches (Fig. 4). A Sentinel-2 image acquired on December 10, 2022, from the Copernicus Open

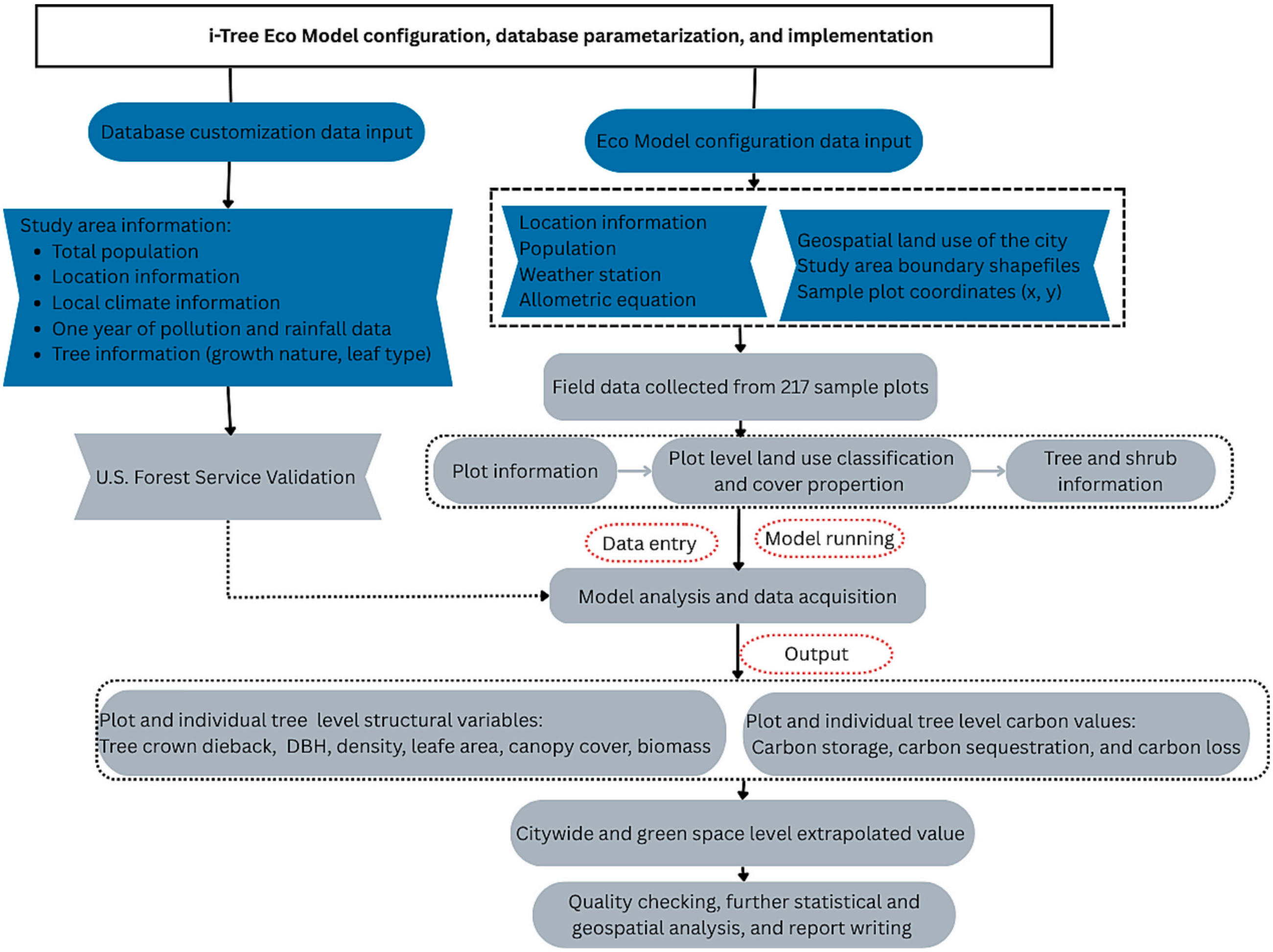

Fig. 3. Extensive customization of the i-Tree tool database and Eco model configuration by manually inputting local climate and location data, tailored to the distinct climate and vegetation of the study area.

Access Hub[1] was used to map the current land use and land cover of the city. This multispectral image, comprising several bands with spatial resolutions ranging from 10 to 60 m, had already undergone radiometric, geometric, and atmospheric corrections [21]. To enhance spatial detail, all bands were resampled to a uniform resolution of 10 m. Land cover classification was then conducted using supervised classification based on the machine-learning algorithm in ArcGIS Pro. Moreover, the spatial distribution of C storage across land uses was determined by extrapolating plot-level estimates to the city scale using the Inverse Distance Weighting technique.

Sampling design and data collection methods

We prepared geospatial data—including administrative boundaries, general land use shapefile, and randomly distributed sample plots before fieldwork and integrated into the Eco model. To ensure representative sampling, the study area was stratified by land use zoning into distinct urban morphological types prior to plot selection and data collection (Fig. 5). All identified urban green space types within each stratum are listed and described in Table 1. Following the i-Tree Eco protocol, detailed land use categories obtained from the city administration were regrouped based on their similarity. Subsequently, we randomly distributed 217 random center points across the land use strata to collect the required data (Fig. 5). As a rule of thumb, at least 200 plots are required to analyze the entire urban forests of stratified random samples of a city, whereas a minimum of 20 plots need to be allocated per stratum [22–23]. The number of plots per stratum was determined based on the extent of tree coverage, with higher coverage resulting in a greater allocation of plots [38]. These points were buffered with an 11.34 m radius to cover the minimum plot area requirement of 400 m^2 [11]. Pre-fieldwork geospatial analysis using high-resolution Google Earth imagery (2022) was conducted to locate the sample plots and gather general information of these samples. This facilitated the visual assessment of land use and land cover types, and cover proportions of each plot during ground-based field data collection.

In each plot, data collection included trees and shrubs information, ground cover characteristics, land use type and general plot attributes was performed [22]. The common, scientific, and local names of tree and shrub species were also assessed and verified with the assistance of foresters and botanists. The species were cross-referenced with Bekele-Tesemma [4], considering their origin, leaf type, growth nature and other characteristics. Measurements such as DBH for single-stemmed trees and individual stem DBH for multi-stemmed trees were taken using calipers. Tree and bole heights were recorded with a clinometer and a wooden stick, respectively, whereas crown width was determined by measuring the north–south and east–west canopy spreads. To estimate the canopy missing, we assessed the percentage of foliage lost due to pruning, dieback, defoliation, uneven crowns, or sparse/dwarf leaves.

Other important variables for this study such tree canopy cover and leaf area were derived from the field measured variables. Specific algorithms in the model utilize these field-measured tree metrics to assess

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[1] Copernicus Data Space Ecosystem | Europe’s eyes on Earth.

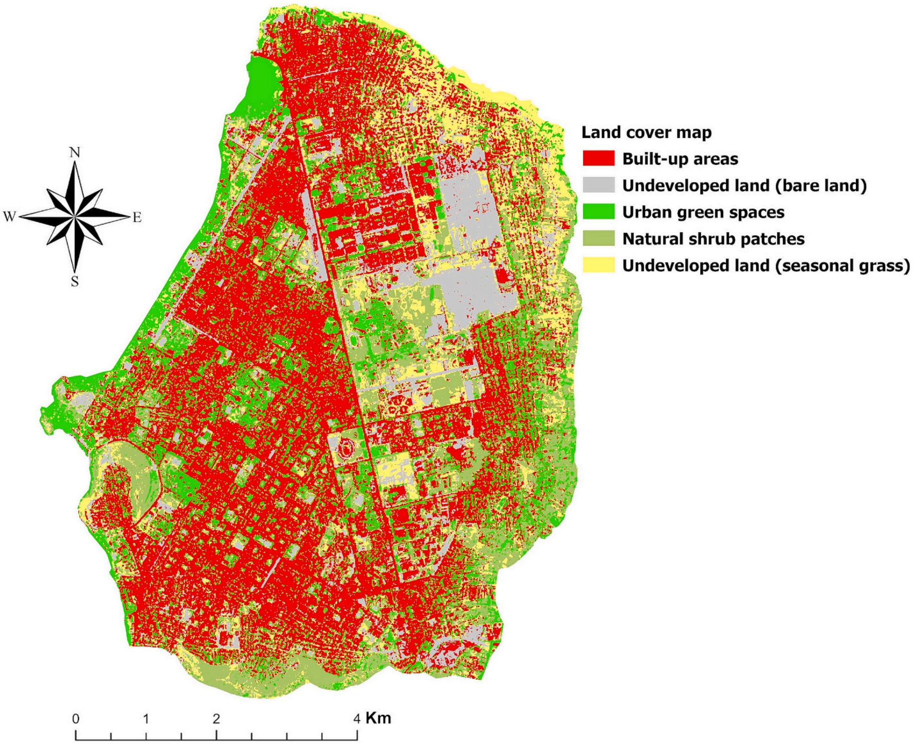

Fig. 4. Land surface cover classification of the built-up region of Hawassa, shows the spatial distribution of built-up areas, green spaces, barren land and seasonal grass in vacant spaces, and other natural shrub patches.

TCC using its established regression equations. Moreover, leaf area index (LAI) was estimated using Module A, a program integrated in the Eco 6.0 model, whereas regression equations estimate the LA of individual trees [18].

Tree biomass estimation

We configured the model to align the surveyed trees with the appropriate allometric equations by integrating detailed tree species information into database. The selected allometric equations, integral component of the model, predict the aboveground biomass (AGB), which is then converted to total tree biomass by multiplying this carbon pool by a factor of 1.26, reflecting a root-to-shoot ratio of 0.26 [39]. To account for the lower AGB of open-grown urban trees compared to forest-grown ones, traditional biomass equations can overestimate biomass in urban settings [35]. Thus, a correction factor of 0.8 was applied to trees recorded in built-up areas (e.g., street trees) to reduce the predicted biomass by 20 %, while trees in forest-like patches (e.g., closed urban parks), similar to those in rural areas, did not require a correction factor. Fresh-weight biomass equations were adjusted using species-specific conversion factors, based on average moisture content values of 0.48 for conifers and 0.56 for hardwoods, to determine dry-weight biomass [39].

Tree carbon storage and sequestration

About 50 % of the total estimated tree biomass is assumed to be carbon, based on global default values provided by the Intergovernmental Panel on Climate Change [20]. As such, the dry-weight biomass was converted to total C storage by multiplying by the carbon conversion factor from IPCC. The monetary value of stored carbon was estimated at \$1.17 per ton, based on the marginal social costs of CO_2e emissions set by the Ethiopian government [52].

Gross carbon sequestration was estimated by updating DBH increment of trees in the model using an assumed growth rate. Carbon sequestration was calculated as the difference in C storage between consecutive years, determined by subtracting the C stored in the current year from that in the following year [36]. Given Ethiopia's 365 frost-free days, the default DBH increment in the model was adjusted using the question:

$$\text{Growth rate} = SGx\frac{N}{153} \tag{1}$$

where *N* stands for number of frost free days of the study area, while SG represents the model's default standard growth rates for areas with 153 frost-free days. The SG (0.58 cm/year for slow, 0.84 cm/year for moderate, and 1.09 cm/year for fast-growing trees) were adjusted for Hawassa's urban trees. The growth rate (fast, slow, and medium) and related characteristics of each tree species was supplemented using information from Bekele-Tesemma [4], which provides detailed descriptions for tree and shrub species across various agro-ecology in Ethiopia. Moreover, growth adjustments considered crown light exposure, with scaling factors of 0.44 for closed forests, 0.56 for urban parks, and 1 for open-grown trees (see [36] for more details).

Tree condition was assessed based on dieback percentage recorded in the field and categorized into different health classes. Mortality rates were adjusted according the percentage of crown dieback, with lower rates for healthier trees and higher rates for those in declining condition [39]. The carbon losses from the tree decomposition were then estimated as:

$$E_c = CxM_cx\sum pi\left((D_{remove}) + (D_{stand})\right) \tag{2}$$

where E_c represents the amount of carbon (t C) emitted from individual trees due to decomposition and removal, C is carbon storage (t) in the consecutive year; M_c mortality likelihood of a particular condition class; pi is proportion of land use tree population in decomposition class i; D_{remove} and D_{stand} represent carbon released from removed dead tree and during decomposition of dead trees still unremoved from the green spaces, respectively. The procedures to estimate D_{remove} and D_{stand}

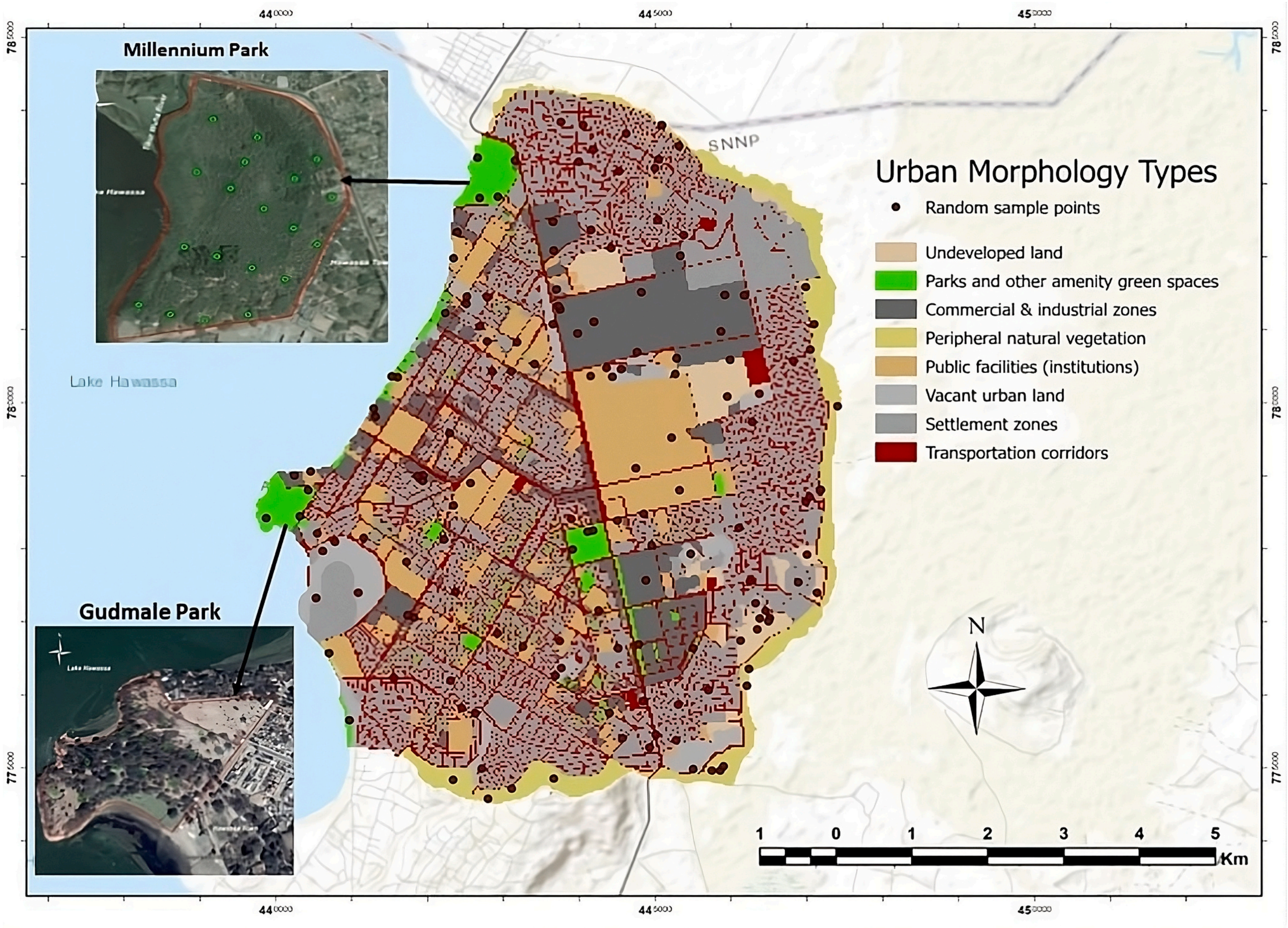

Fig. 5. Classification of urban morphological types and general land boundaries, highlighting urban form patterns and the layout of the city's land use, including the two main urban parks of the city.

(direct outs of the model) using the corresponding algorithms in the Eco model are detailed in Nowak et al. [39]. In the end, the net carbon sequestration was derived by subtracting total carbon loss from gross carbon sequestration.

We assessed the carbon-offsetting role of the urban green spaces by comparing Hawassa's total GHG emissions with the amount of carbon removed through carbon sequestration. The emission data for Hawassa were obtained from the Emission Database for Global Atmospheric Research[2] [7], which directly estimates country- and city-level emissions. Furthermore, we evaluated their emission-offset potential by estimating the number of individual residents whose annual emissions could be mitigated by the total CO_2e removal achieved through the net carbon sequestration. This was calculated by dividing the annual t CO_2e removed by the total GHG emissions attributed to the city's population, based on Ethiopia's national per capita GHG emissions. There have been various per capita emission values reported for Ethiopia, depending on the types GHGs and the emitting sectors considered in the calculations. However, we adopted the value of 1.63 t CO_2e for 2022 reported by Crippa et al. [6], encompassing CO_2, CH_4, N_2O, and F-gases from all sectors. For this purpose, only the total urban population in 2022—excluding rural districts—was used, based on projections from the 1999 census.

Soil and litter sampling and carbon analysis

Urban soil sampling is challenging due to soil compaction and ongoing land use changes. Hence, high methodological uncertainties are expected to determine the soil organic carbon (SOC) analysis in urbanized areas. As such, we conducted SOC and litter carbon analysis in two enclosed forest-like urban parks—Gudmalle Park, dominated by native species, and Millennium Park, which contains a mix of native and exotic vegetation—using protocols similar to those applied in natural forest studies. It is worth noting that, despite the methodological uncertainties, Feyisa et al. [9] studied the SOC of urban green spaces of Hawassa, excluding the parks selected in the present study.

We randomly distributed a total of 13 circular plots in a native-dominant park and 19 in a mixed park, each covering 400 m^2, for sampling (Fig. 5). In each plot, 0.25 m^2 subplots were established using a 0.28 m radius for litter and soil sampling. For SOC determination, soil samples were collected using a soil auger from the four corners of the main plot to a depth of 40 cm, then collected composite subsample, sun air-dried, and sieved (<2 mm) for analysis[15]. Soil carbon concentration was measured using the Walkley-Black method. Similarly, litter samples were collected from the same subplots. Fresh weight was recorded, and a 100 g composite subsamples were taken and oven-dried at 65 °C for carbon analysis following the Walkley-Black method [56].

SOC was calculated based on the oven-dried weight of soil from known sampler volumes and organic carbon concentrations [41].

$$SOC = \%C * BD * D \tag{3}$$

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[2] https://edgar.jrc.ec.europa.eu/emissions_data_and_maps.

where SOC is soil organic content (t ha^{-1}), %C represents soil C concentration determined in the lab, BD is bulk density (g/cm^3) determined by the average air-dried mass of soil (g) divided by the volume of the core sampler (h x πr^2, cm^3), D is total depth to which the samples were collected from (40 cm).

The litter subsamples that were brought to the laboratory were used to determine the total dry biomass per hectare, following the method by Pearson et al. [41].

$$BM_L = \frac{W_{field\_}\text{subsample}}{A} * \left[\frac{W_{dry\_}\text{subsample}}{W_{fresh\_}\text{subsample}}\right] * \frac{1}{10,000} \tag{4}$$

BM_L is the dry biomass of dead litter (t ha^{-1}); $W_{field_}$subsample represents the fresh field sample of litter collected in the subplot of 0.25 m^2 area; A is the area of the subplot in which sample litter was collected and converted to hectare (0.000025 ha); $W_{dry_}$subsample is the weight of the oven-dried weight of litter. The total litter C stock (t ha^{-1}) is quantified by multiplying the dry biomass of the dead litter by the carbon concentration in the litter determined in the laboratory.

Statistical analysis

All data analyses were performed in R. Plot-level tree metrics (DBH, TCC, LA) and tree density in each plot, derived from the model, were aggregated and averaged. We evaluated the normality of our data using Shapiro-Wilk test, revealing a violation of the assumption. As a result, we applied Spearman's rank correlation, a non-parametric method suited for non-normal data, to explore the relationship between changes in tree metrics and spatial variations in C storage [25].

Results

Biophysical environment of Hawassa

The predominant land surface cover of Hawassa was impervious cover (45.7 %), with water covering <1 %. Fig. 5 illustrates land cover classes of Hawassa, categorized into built-up areas, vacant land with exposed soil (barren land) and season grass, manmade green spaces, and natural shrub patches. Built-up areas dominate the oldest parts of the city, particularly in the central and northern regions, where the minimal vegetation cover was recorded. In contrast, vegetation cover was predominantly located in the western part, characterized by community gardens, closed parks, and government institutions. Specifically, street trees (STS) had the highest impervious cover, reflecting minimal green space, while unmaintained natural vegetation in the in the natural area (UGS) had the lowest, with a significant portion covered by natural grasses. In contrast, STS had minimal grass due to high concrete, amenity green spaces, parks, recreational (RGA) had extensive barren land, and scatter vegetation in vacant spaces (VUL) combined high impervious cover with notable grass (Table 2).

In the native Park, 14 tree species contribute to 58 % of the forest cover, with bare land covering 4 % and grassland making up 38 %. In contrast, the mixed Park, home to 17 woody species, accounts for 77 % of the forest cover, while bare land and grassland cover 13 % and 10 %, respectively. Notably, 86 % of the tree species in the native Park and 65 % in mixed Park were native. The distribution of tree and shrub cover also varies across the green space, ranging from the lowest in UGS at 19.9 %, where grass is the most prevalent cover, to the highest in RGA at 49.4 %. The highest tree mortality rates were recorded in business district green spaces (BDS) at 18.4 % and public facility green spaces (PFS) at 17 %, primarily due to overaged trees. In contrast, undeveloped green areas (UGA) showed minimal decline (0.6 %), likely due to lower urbanization intensity. More than 70 % of the trees in Hawassa were concentrated within the 0–7.6 cm DBH class, indicating a dominance of younger trees with relatively low current C storage but high potential for future sequestration as they mature. On the other hand, 57 % of trees in UGA and 49.5 % in UGS in the smallest DBH class, while 36.9 % and 41 % of trees in settlement areas fall into the first and second DBH classes, respectively.

Carbon density across the green spaces of Hawassa

The urban green spaces in Hawassa stored 62,439.6 tons (229,153.33 t CO$_2$e), with an economic value of $268,109.81 (Table 3). Urban green space clusters like PFS and RGA contributed more than 58.2 % of this total. Annual gross C sequestration was estimated as 5,339.3 t C ha^{-1} yr^{-1} (19,595.23 t CO$_2$e), with net sequestration of 4,613.4 t C ha^{-1} yr^{-1} (16,931.2 t CO$_2$e) after accounting for 779.9 t C lost due to decomposition. This means approximately 86.4 % of gross

Table 3
Summary of carbon metrics estimated for the UGrS in Hawassa (southern Ethiopia): total C storage (t), gross sequestration (t yr.$^{-1}$), total carbon loss (t), net sequestration (t yr.$^{-1}$), and monetary values for the total carbon storage in each cluster.

UGrS	Total C storage	Gross C sequestration	Net C sequestration	Total C loss	Storage values ($)
PFS	24,515.1	1,187.86	980.9	207.0	28,682.7
RGA	11,839.7	434.62	296.6	138.0	13,852.5
GSS	7,666.6	1,818.93	1,763.5	55.4	8,970.0
BDS	7,492.9	483.94	214.2	269.8	8,766.6
STS	5,282.5	57.23	636.0	98.9	6,180.5
VUL	3,847.2	271.65	264.2	7.4	4,501.3
UGA	931.1	201.96	200.0	2.0	1,089.4
UGS	864.5	259.41	258.0	1.4	1,011.5

Table 2
Green space clusters (GSC) characteristics including the current mortality rate, land surface cover proportion, and other urban tree attributes in Hawassa, southern Ethiopia.

GSC	Land surface cover (%)				Tree and shrub attributes			Leaf area index
	Impervious	Barren land	Grass	Water	Mortality (%)	Cover (%)	Density (ha^{-1})	
PFS	40.5	18.3	38.4	2.9	17.0	37.60	115.31	2.4
RGA	16.5	33.8	43.9	5.8	4.6	49.4	165.32	3.5
GSS	53.1	24.9	22.0	0.1	3.0	21.7	120.46	0.6
BDS	47	14.9	38	0.1	18.4	21.5	41.75	0.4
STS	59.8	27.7	12.6	0.0	8.7	19.1	115.07	0.5
VUL	45.3	15.4	33.2	6.1	3.6	24.1	89.24	0.7
UGA	11.7	52	36.3	0.0	0.6	20.1	190.29	0.7
UGS	1.6	27.7	68.2	2.6	1.1	19.9	114.95	0.4

PFS: Green spaces in public facility areas (e.g., institutional green areas, church forests), RGA: Recreational green spaces including designed and natural parks, neighborhood community, and lakeside green spaces, GSS: Green spaces in residential areas (e.g., residential forests), BDS: Green spaces in business district centers, industrial, and commercial areas, STS: Urban trees along streets, roads, and other transportation related areas, VUL: Vacant urban and public land, and shrub patches in the inner city, UGA: A land designated as green spaces but not properly developed in the inner city (e.g., urban agriculture), and UGS: Natural land at the periphery of the city with no management application (e.g., green belt).

remained to offset GHG emissions. Carbon loss varied by tree health, with the highest loss in BDS and PFS, where many trees were dead or in poor or critical health condition, while the lowest loss was observed in UGS due to less tree mortality (Table 2 and 3).

We standardized values by calculating carbon density, which reflects carbon concentration per unit area of land or TCC. Carbon storage hotspots were identified across Hawassa using spatial interpolation, with higher values up to 179.74 t ha^{-1} in areas with minimal grey cover (Fig. 6). These hotspots corresponded to dense vegetation, especially urban green spaces with large native trees in parks and community gardens. In contrast, the central and eastern parts of Hawassa had much lower C storage, down to 1.74 t ha^{-1}, due to the prevalence of built areas and barren land.

This study found significant variations in carbon dynamics across urban green spaces clusters (Table 4), with mean C tree storage 12 t C ha^{-1} land and 5.8 kg C m^{-2} TCC for the entire city. Mean carbon density ranged from 2.9 to 60.72 t C ha^{-1} by land, and 20.54 to 137.67 t C ha^{-1} by TCC. RGA had the highest total C storage (60.72 t C ha^{-1} land, 137.67 t C ha^{-1} TCC), while UGS contributed the least, mainly due to small shrubs. Similarly, RGA also had the highest gross C sequestration (2.23 t C ha^{-1} yr^{-1} land), while UGS led with 7.31 t C ha^{-1} yr^{-1} TCC.

We identified tree species as top carbon reservoirs based on their stored and sequestered carbon (Appendix A), with carbon density ranging from 0.00 t C ha^{-1} (*Prunus persica*) to 3.18 t C ha^{-1} (*Ficus sur*). The carbon dynamics of the top 15 tree species in the study area, which contributed about 87 % of the total carbon storage, are presented in Fig. 7. Among native broadleaved deciduous trees, *F. sur* (3.18 t C ha^{-1}), *Faidherbia albida* (0.92 t C ha^{-1}), and *Cordia africana* (0.38 t C ha^{-1}) exhibited the highest carbon storage. In terms of annual carbon sequestration, non-native species such as *Casuarina equisetifolia* (102.07 t C ha^{-1} yr^{-1}) and *Grevillea robusta* (0.23 t C ha^{-1} yr^{-1}) performed better. Some native species like *F. sur* (0.01 t C ha^{-1} yr^{-1}) and *C. africana* (0.04 t C ha^{-1} yr^{-1}) contributed modestly, while others, including *F. albida* (−0.008 t C ha^{-1} yr^{-1}) and *Celtis africana* (−0.002 t C ha^{-1} yr^{-1}), showed negative sequestration values—most likely due to tree decline or biomass loss.

Table 4

Quantified total Carbon density (Mean ± SE) for each green space clusters by unit area of land (tC ha^{-1} land) and tree canopy (tC ha^{-1} TCC) respectively, and C loss (kg ha^{-1}).

Green space clusters	Total C Storage		Gross C sequestration		Net C sequestration		C loss
PFS	33.93 ± 14.32	97.51	1.64 ± 0.45	4.72	1.36	3.90	286.41
RGA	60.72 ± 13.46	137.67	2.23 ± 0.47	5.05	1.5	3.45	707.26
GSS	3.88 ± 0.75	20.54	0.92 ± 0.16	4.87	0.89	4.72	28.18
BDS	11.05 ± 5.71	72.68	0.71 ± 0.32	4.70	0.32	2.08	397.92
STS	5.50 ± 1.30	33.54	0.77 ± 0.04	4.67	0.66	4.04	102.94
VUL	18.95 ± 10.19	95.23	1.34 ± 0.59	6.73	1.30	6.54	37.62
UGA	5.61 ± 2.65	32.61	1.23 ± 0.45	7.07	1.2	7.00	9.89
UGS	2.90 ± 1.35	24.38	0.87 ± 0.40	7.31	0.87	7.27	5.19

Urban tree attributes effects on carbon storage

Tree metrics drive C storage and sequestration variations across land uses. Statistically, strong positive correlations were found between C storage and DBH ($r = 0.80$, $p < 0.001$), LA ($r = 0.75$, $p < 0.001$), and TCC ($r = 0.71$, $p < 0.001$), indicating that larger DBH, greater LA, and higher TCC contribute significantly to higher C storage (Fig. 8). Tree density also showed a positive, though weaker, correlation with C storage ($r = 0.31$, $p = 0.05$). The smallest DBH class (0–7.6 cm) had the highest tree density (309.3 ha^{-1}), contributing over 28 % to total C storage. Larger DBH classes (15.2–61 cm) had moderate C storage due to fewer trees, while the largest class (76.2–106.7 cm) exhibited higher C storage per tree but limited overall contribution due to low density (3 trees ha^{-1}), with 216 t C storage and 10 t C yr^{-1} sequestration.

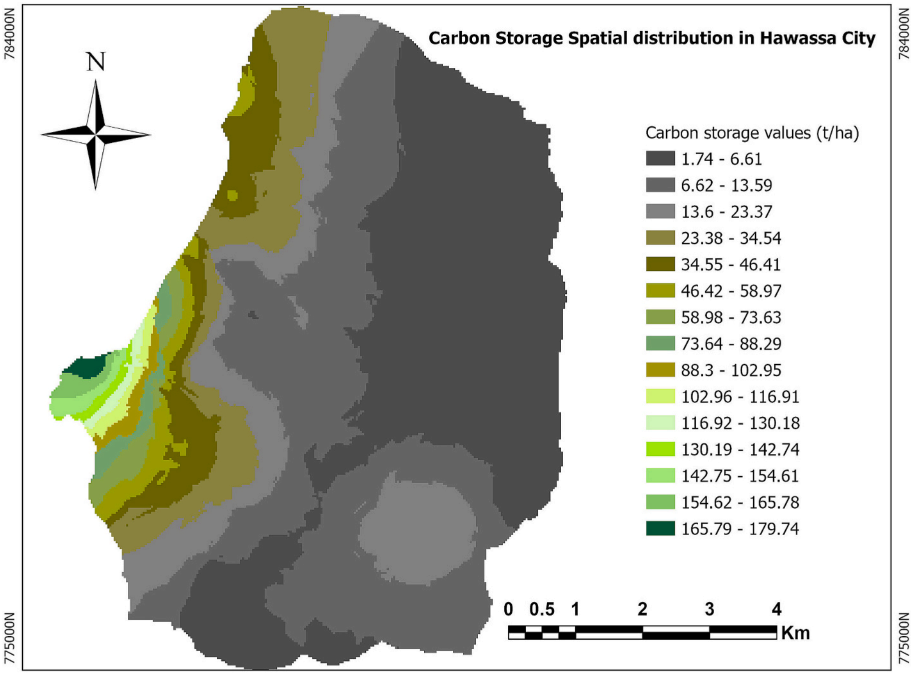

Fig. 6. Spatial pattern of carbon storage (t C ha^{-1}) in urban tree biomass across the green spaces of Hawassa, varying with land use type, urbanization level, and tree cover.

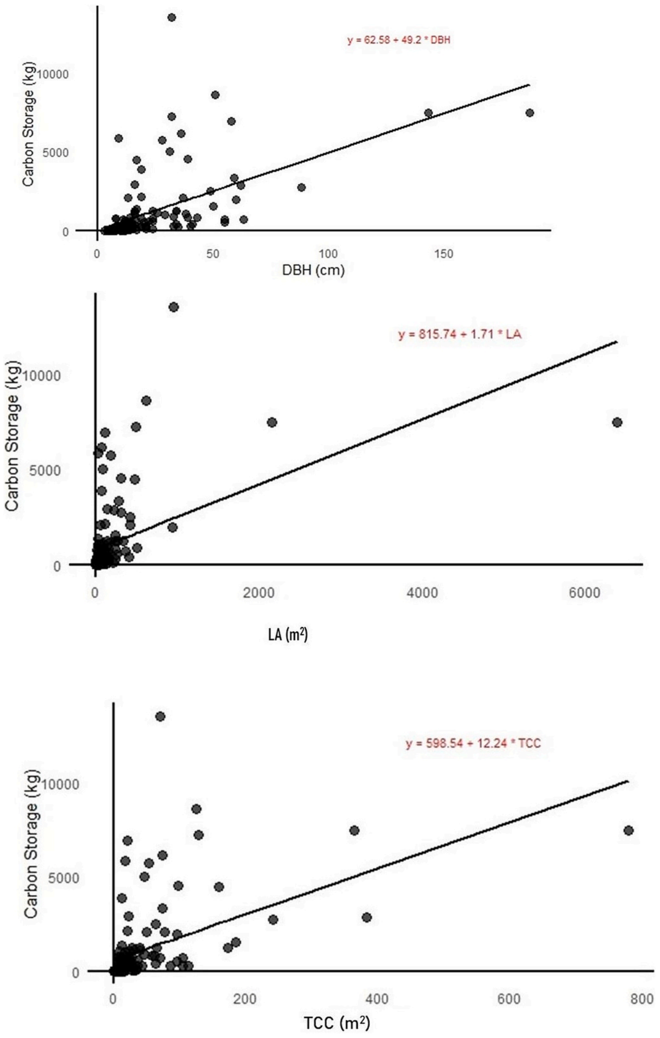

Fig. 7. Mean carbon storage, carbon loss, and net carbon sequestration of the top 15 tree species in the Hawassa (southern Ethiopia), highlight the contributions of individual species to carbon dynamics.

Litter and soil carbon density of urban parks

The total SOC for the native species-dominated park (Park 1) was estimated as 6,953.2 t C (25,518.2 t CO_2e) with dead litter C of 39.1 t C (143.6 t CO_2e), while the mixed-species (Park 2) had a total SOC of 8,806.2 t C (32,318.6 t CO_2e) and litter C of 50.9 t C (186.7 t CO_2e) (Table 5). The mean carbon density of dead litter across both parks ranged from 0.26 to 3.99 t C ha^{-1}, while soil carbon density varied from 96.5 to 284.04 t C ha^{-1}. SOC density for both parks was 189.8 t C ha^{-1}, with a mean dead litter C stock of 1.08 t C ha^{-1}. Park 1 showed a higher mean SOC (204.5 ± 14.2) compared to Park 2 (179.7 ± 10.2), indicating that native trees in Park 1 contribute more to SOC. Litter carbon was also slightly higher in Park 1, suggesting a marginally greater contribution to C storage. Comparing mean SOC to tree biomass carbon, SOC was notably higher, highlighting urban soils as a key carbon pool.

Discussion

Carbon offsetting roles of urban green spaces

Ethiopia's national carbon budget often overlooks the climate regulation roles of urban green spaces, despite contributions sometimes comparable to nearby natural ecosystems. Omitting them from spatial

Table 5
Comparison of mean carbon storage (Mean ± SE) and CO_2e values for three carbon pools—dead litter and soil in two natural parks, and tree carbon storage at city level in Hawassa, southern Ethiopia.[1],[2].

Categories	Carbon pool	Mean ± SE (tC ha^{-1})	$C_{max.}$ (tC ha^{-1})	$C_{min.}$ (tC ha^{-1})	Mean CO_{2e}
Native Park [1]	Litter	1.40 ± 0.31	4.55	0.30	5.00
	SOC	204.5 ± 14.20	284.00	96.50	750.50
Mixed Park [1]	Litter	1.20 ± 0.10	23.10	0.40	4.50
	SOC	179.7 ± 10.20	273.80	123.90	659.60
Across both Parks	Litter	1.08 ± 0.12	3.99	0.26	3.96
	SOC	189.8 ± 8.50	284.04	96.46	696.57
All strata	Urban tree	12.01 ± 2.25	60.70	2.90	65.30

[1] Native species dominant enclosed Park, characterized by minimal intervention and preservation of Indigenous vegetation.

[2] Park with a combination of native and exotic tree species, reflecting a modified or managed urban green space.

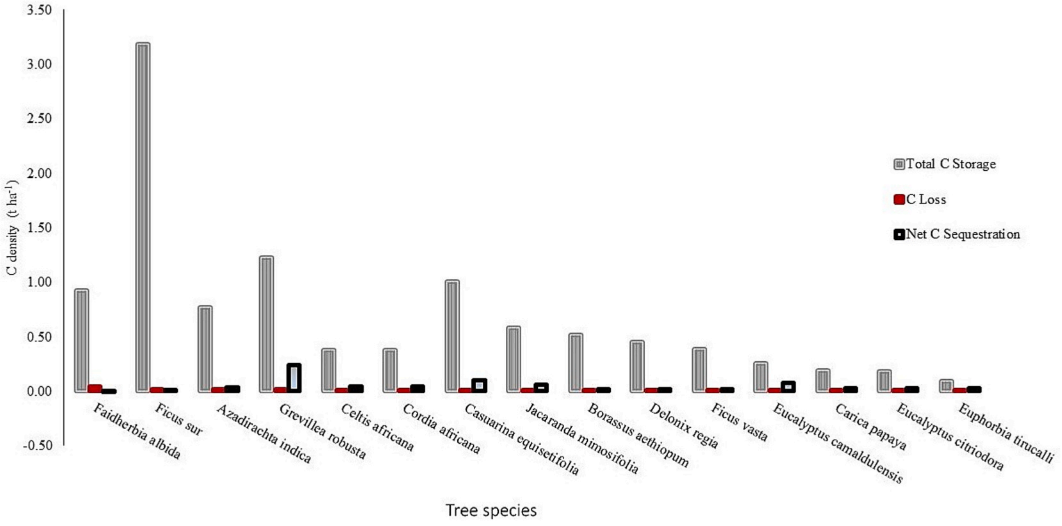

Fig. 8. Scatter plots show positive correlations between carbon storage and tree metrics (dimeter size, leaf area, tree canopy cover).

planning limits their potential for climate change mitigation [17]. Recently, Ethiopia signed an Emission Reductions Purchase Agreement to cut emissions by 4 million t CO_2e (2022–2029), targeting 0.5 million t CO_2e annually [60]. Our analysis shows that Hawassa's green spaces C sequestration could contribute 3.4 % of this national reduction commitment.

Moreover, urban green spaces in Hawassa, including soil and litter C in parks, have mitigated 286,990.3 t CO_2, and their annual sequestration could offset 4.9 % of the city's total emissions (346,598.2 t CO_2e)—nearly doubling the mitigation achieved by Barcelona's urban forests [3]. This difference may be attributed to the higher GHG emission typical of larger cities like Barcelona, as well as favorable climatic conditions in Ethiopia that support continuous tree growth and carbon sequestration throughout the year. Based on Ethiopia's national per capita emissions, the total net carbon sequestration by urban green spaces in Hawassa could offset the annual emissions contributed by approximately 3.23 % of the city's population. These findings suggest that exploring the C storage potential of urban green spaces in cities of similar size to Hawassa across Ethiopia and beyond in the Sub-Saharan Africa could substantially contribute to support national and regional mitigation efforts.

Carbon reservoir alternatives for urban areas

Urban soils play a crucial role in C storage, with variations depending on land use and vegetation composition. The native-dominated park exhibited the highest mean SOC (204.5 ± 14.20 t C ha^{-1}), surpassing the mixed park (179.7 ± 10.20 t C ha^{-1}). This difference is likely due the continuous litter fall and shading by native deciduous trees, which enhance under-canopy SOC [57]. In the native park, soil and litter samples were collected exclusively under or near native trees, while in the mixed park; plots were located under mixed species and on barren land (Appendix B). Wang et al. [57] found that SOC increased with proximity to native trees in Newcastle, UK, likely due to the higher quality and continuous organic matter input. This underscores the role of preserving indigenous species and avoiding monocultures to enhance urban soil C stocks.

The mean SOC across parks (189.8 ± 8.50 t C ha^{-1}) closely aligns with the global maximum urban SOC average (188.6 ± 115.7 t C ha^{-1}) across various climates [14]. Urban parks with limited accessibility stored more carbon than the green spaces in the built area of Hawassa, such as institutional green spaces (111.5 ± 27 t C ha^{-1}), street trees (97.6 ± 15.1 t C ha^{-1}), and church forests (97.3 ± 31.1 t C ha^{-1}) [9]. In this study, soil is the dominant carbon pool, far exceeding the mean C stored in the tree biomass (12.01 ± 2.25 t C ha^{-1}) and litter (1.08 ± 0.12 t C ha^{-1}). Our result was aligned with studies conducted in Kumasi, Ghana [34]and New York City, USA [42], where soils were reported as the primary carbon reservoir. However, soil carbon contributions highly dependent on soil type, vegetation cover, and other factors, emphasizing the need for their consideration in urban development [14].

Litter carbon storage values independently estimated for the native and mixed parks in Hawassa were comparable, with mean values of 1.40 ± 0.31 t C ha^{-1} and 1.20 ± 0.10 t C ha^{-1}, respectively. However, cumulative mean litter carbon across the two urban parks was estimated as 1.08 ± 0.12 t C ha^{-1}, which is comparable to tropical dry forest carbon values estimated at 2.1 t C ha^{-1} [20] but lower than urban church forests (17.83 t C ha^{-1}) in Addis Ababa [53]. This lower value likely results from faster litter turnover in urban settings due to human activities and climatic influences on decomposition. This lower storage capacity may reflect faster litter turnover in urban environments due to human activities and climatic factors influencing decomposition rates [63].

Urban tree's carbon densities

The estimated tree carbon density in Hawassa's urban green spaces (12.01 t C ha¯1) exceeds that of Los Angeles, USA (8.15 t C ha¯1) but is closely aligned with Sacramento, USA (15.4 t C ha¯1) [31]. Notably, Hawassa's values (12.01 t C ha¯1 land; 5.8 kg C m¯2 TCC) closely comparable to those of Leipzig, Germany (11.8 t C ha¯1; 6.82 kg C m¯2) despite climatic differences [48], likely due to their similar tree canopy cover: 19 % in Leipzig vs. 20.7 % in Hawassa. While our methodology aligns with studies in the Global North, the distinct climate of Sub-Saharan Africa may affect the direct comparisons.

On the other hand, differences in methodologies used to estimate C storage in urban forests across sub-Sub-Saharan Africa cities may influence comparisons. For example, Hawassa's urban tree carbon density (12.01 t C ha¯1) is only 16.68 % of the sub-Saharan tropical dry forest average (72 t C ha¯1) reported by the IPCC [20]. In contrast, the urban green spaces in Dessie city of Ethiopia, with slower urbanization, reported an exceptionally high carbon density of 745.17 t C ha¯1 [33]. Similarly, Addis Ababa's mountainous urban forests showed higher carbon densities (172 t C ha¯1), although inner city urban green spaces were not considered in the analysis [59]. However, these studies used allometric equations developed for forest-grown trees, which may not fully capture urban forest characteristics. Likewise, carbon densities reported in other African cities, such as Kumasi, Ghana (211.28 t C ha¯1), and Nador, Morocco (41.63 t C ha¯1), were significantly higher than in our study [34,43]. These values were also estimated using allometric equations derived from rural forests, highlighting the need for urban-specific equations that account for the unique conditions of urban landscapes, such as those used in this study. Applying rural-based models in urban settings without correction factors may lead to overestimation, as urban tree aboveground biomass tends to be lower than that of forest trees of the same DBH due to open growing conditions [39], 2013).

Effects of urban development on carbon dynamics

Urbanization is closely linked to land surface cover, with highly urbanized areas characterized by impervious surfaces, while less urbanized regions tend to have greater vegetation cover [28]. The land cover and carbon dynamics maps in this study highlight areas with high C storage potential in areas with higher vegetation cover, showing urbanization's impact (Figs. 5 and 7). Manmade urban green spaces and natural shrub patches in the west and southwest exhibit the highest C storage (179.74 t C ha^{-1}), whereas strata predominant by built-up and barren lands store significantly less (≤1.74 t C ha^{-1}) due to minimal vegetation. This aligns with Sun et al. [49], who found a strong negative correlation between urbanization and C storage. The dominance of impervious surfaces underscores the need for innovative urban greening strategies, such as green roofs and vertical gardens, to address land scarcity and enhance carbon storage in the Sub-Saharan Africa cities.

Urban green spaces with high vegetation cover and low impervious surfaces stored the most carbon. For example, neighborhood green spaces and urban parks together with16.5 % impervious stored 60.72 ± 13.46 t C ha^{-1} —surpassing some rural forests, such as 22.3 t C ha^{-1} in traditional agroforestry in Ethiopia [12]. However, Hawassa's overall carbon density (12.01 t C ha¯1) is significantly lower than rural estimates, likely due to reduced tree cover and density [37]. This suggests that urban forests can occasionally exceed rural forests in C storage potential [42], particularly in less disturbed parks and religious areas with mature trees and greater canopy cover.

Effects of urban tree metrics on the carbon storage

This study highlights the remarkable roles of tree-specific attributes in the spatial variation of C storage and sequestration across Hawassa. Our statistical analysis revealed strong correlations between C storage and DBH, LA, and TCC. While the positive correlation between tree density and C storage ($r = 0.31$, $p = 0.05$) suggests that denser tree populations contribute to C storage, the relatively weak correlation underscores the importance of other factors. This implies that tree health and size play a more dominant role, as larger, healthier trees store more carbon, regardless of density. Young trees with higher densities in urban agriculture and residential green spaces contributed over 28 % of total C storage due to their abundance, while mature trees in recreational green spaces (urban parks and other amenity green spaces) and public facility green areas, characterized by higher density and cover, dominated C storage. Spatial variation in TCC influences C storage potential, with amenity green spaces and parks (44.1 % TCC) storing the most carbon, while green spaces in industrial areas and street greeneries, due to sparse TCC and high mortality rates, retained the least. The higher C storage and sequestration in these areas is attributed to large native broadleaved species, which typically possess greater biomass [29].

Higher tree mortality rates in some green spaces, such as 17 % in institutions and 18.4 % in residential areas, contribute to greater carbon losses, underscoring the need for effective management strategies to reduce mortality and sustain carbon dynamics. This is particularly concerning because most tree species with negative net sequestration values were recorded in these areas. In Hawassa, overaged native species (e.g., *F. albida*: -8.06 t C ha^{-1} yr^{-1}, *C. africana*: -1.99 t C ha^{-1} yr^{-1}) exhibited negative net sequestration, indicating that carbon loss exceeded absorption. While overaged native tree species exhibited greater carbon loss, fast-growing exotic species were more effective in carbon sequestration. In contrast, slow-growing native species excelled in long-term carbon storage, reinforcing the importance of preserving large, mature and native trees with high longevity and biomass potential.

Uncertainties

Despite the use of customized models, uncertainties remain in applying the Eco model to quantify C storage and sequestration. A key source of uncertainty is the possibility of reliance on allometric equations at the family level rather than species-specific equations, potentially leading to biomass estimation inaccuracies. Additionally, the model merges C storage and sequestration values for aboveground and belowground carbon pools, limiting the ability to assess them separately.

While emission data for all sectors of the city are available in the Emission Database for Global Atmospheric Research, emissions from commercial building sector are missing. We adopted a proxy-based scaling approach using emission data from similar cities in Ethiopia [10]. This method estimates emissions by adjusting building emission values estimated for Addis Ababa city (Sani [45], the capital of Ethiopia. It is acknowledged that direct, building-specific emission measurements using advanced tools would yield results that are more precise. However, such measurements were beyond the scope of this study and would require a separate and specialized effort, highlighting the need for future research to generate localized emission data.

The soil carbon analysis in this study focused on less disturbed green systems in Hawassa, as applying conventional methods proved challenging. Urban parks, with their forest-like structure, were selected for the analysis because they are suitable for traditional soil carbon measurement methods typically used in rural areas. However, the lack of standardized methods for estimating SOC in highly urbanized areas, where green spaces vary significantly in structure and composition, presents a major challenge. Furthermore, the Eco model does not assess the role of trees in mitigating emissions from urban buildings by enhancing energy efficiency. This limitation arises because the model was designed with building types in the U.S. in mind and does not consider the specific context of Ethiopia. These methodological uncertainties hinder the comprehensive investigation of urban green spaces contributions to emission reductions through improved building energy efficiency. Consequently, these limitations may have led to an underestimation of the climate regulation potential of Hawassa's urban green spaces.

Conclusion

Our findings show that urban green spaces substantially contribute to mitigating the climate footprint of urbanization, primarily through C storage and sequestration. These natural systems serve as vital carbon sinks amid rapid urban expansion. This study highlights the untapped potential of urban green spaces in Ethiopia as a valuable asset for climate mitigation and even carbon credit generation at local, regional, and national levels. However, the effectiveness of these contributions is influenced by vegetation structure, land use type, and the degree of fragmentation of green spaces. We identified that areas with lower impervious surfaces, greater canopy cover, and native broadleaved tree species—particularly in less fragmented urban forests—have the highest carbon storage capacity, with values ranging from 30–60 t C ha^{-1} and annual sequestration rates between 1.4–1.5 t C ha^{-1} yr^{-1}.

While every urban carbon pool deserves attention, preserving soil quality is critical, as native urban soils store significant carbon. Moreover, although forest in cities store less carbon per land area than those in the periurban and rural ones, they may store more per canopy area due to the presence of larger trees. These findings emphasize the importance of integrating soil protection with green infrastructure planning in urban climate strategies.

This study reveals that urban trees per unit area of land contribute less to GHG mitigation than trees in forests. However, urban trees often store more carbon per unit of canopy cover than rural trees due to the higher prevalence of larger tree sizes in cities with wider space [37]. This study suggests that prioritizing the preservation and restoration of urban forests can provide long-term environmental benefits by enhancing C storage capacity in urban areas.

The future seems more difficult as the rapid urbanization throughout the Sub-Saharan Africa appears to be overwhelming the urban landscape with physical structures, leaving little room for greenery. To address this challenge, this study advocates for the integration of green infrastructure into urban planning through innovative and context-sensitive approaches. These strategies have proven to be effective NbS in the Global North [24], offering valuable lessons for their potential application in rapidly urbanizing cities in Ethiopia. Adapting these solutions to local conditions, including the structural suitability of buildings and the choice of appropriate plant species, can enhance urban resilience and contribute to mitigate GHG emissions.

Specific implications to help policymakers and planners successfully translate the findings into practice are:

- Balance grey and green infrastructure by redesigning less performing green spaces in terms of C storage and strategically introducing new ones, particularly in densely built urban areas. This should include a thoughtful mix of native and ornamental tree species to maximize both ecological and aesthetic value, thereby enhancing cities' self-sufficiency in mitigating greenhouse gas emissions.
- Investigate and strengthen national and regional policy frameworks that explicitly support the integration of adequate nature into structural and master plans. This includes integrating green space requirements into land use plans, zoning regulations, and building codes to ensure long-term institutional commitment.
- Converting undeveloped land into well-planned urban green spaces can help address the unequal distribution of ES among urban residents, fostering more inclusive and equitable access to environmental benefits.

CRediT authorship contribution statement

Tikabo Gebreyesus: Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Christian Borgemeister:** Writing – review & editing, Validation, Supervision, Investigation. **Cristina Herrero- Jáuregui:** Writing – review & editing, Validation, Supervision, Investigation.

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.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cacint.2025.100217.

Data availability

Data will be made available on request.

References

[1] Abunnasr, Y. F. (2013). *Climate Change Adaptation : A Green Infrastructure Planning Framework for Resilient Urban Regions (Doctoral dissertation)* [University of Massachusetts Amherst]. https://scholarworks.umass.edu/open_access_dissertations.

[2] Anderson B, Patiño Quinchia JE, Prieto Curiel R. *Boosting African cities' resilience to climate change: The role of green spaces*. In: *West African Papers*. Paris: OECD Publishing; 2022. https://doi.org/10.1787/3303cfb3-en.

[3] Baró F, Chaparro L, Gómez-Baggethun E, Langemeyer J, Nowak DJ, Terradas J. Contribution of ecosystem services to air quality and climate change mitigation policies: the case of urban forests in Barcelona. Spain Ambio 2014;43(4):466–79. https://doi.org/10.1007/s13280-014-0507-x.

[4] Bekele-Tesemma, A. (2007). *Useful trees of Ethiopia: identification, propagation, and management in 17 agroecological zones. Nairobi: RELMA in ICRAF Project, 552p.* RELMA in ICRAF Project, World Agroforestry Centre, Eastern Africa Region.

[5] Cities4Forest. (2019). Success Story f Hawassa City. Available online: https://www.cities4forests.com/city/hawassa/ (Accessed on January 20, 2025). 2019.

[6] Crippa, M., Guizzardi, D., P., F., B. M., Muntean, M., Schaaf E., Becker, W., Monforti-Ferrario, F., Quadrelli, R., Risquez Martin, A., Grassi, G., Rossi, S., Brandao De Melo, J., Oom, D., Branco, A., San-Miguel, J., Vignati, E. , Taghavi-Moharamli, P., & Köykkä, J. (2023). *GHG emissions of all world countries, Publications Office of the European Union, Luxembourg, 2023, doi:10.2760/953332, JRC134504*. DOI: 10.2760/235266.

[7] *Crippa, Monica; Guizzardi, Diego; Pisoni, Enrico; Solazzo, Efisio; Guion, Antoine; Muntean, Marilena; Florczyk, Aneta; Schiavina, Marcello; Melchiorri, Michele; Fuentes Hutfilter, Andreas (2021): EDGAR_emissions_urban_areas. European Commission, Joint Research Centre (JRC) PID:* http://data.europa.eu/89h/c0c49cd7-4a80-4a94-8c34-375289c12b2d. (n.d.).

[8] Ethiopia's Ministry of Planning and Development. (2020). Ethiopia's long-term low emission and climate resilient development strategy (2020-2050). Minister of Planning and Development, Federal Democratic Republic of Ethiopia. Addis Ababa, Ethiopia.

[9] Feyisa A, Negash M, Melka Y. Urban green infrastructure affects woody plant diversity and carbon stock in Hawassa city in Ethiopia. Arboricultural J 2022;44(2):84–98. https://doi.org/10.1080/03071375.2021.2014696.

[10] Fong, W. K., Mary, S., Michael, D., Seth, S., Ana, M., & Chang, D.-B. (2014). *Global Protocol for Community-Scale Greenhouse Gas Emission Inventories (GPC). Washington, DC: World Resources Institute, C40 Cities Climate Leadership Group, and ICLEI – Local Governments for Sustainability, 2014*.

[11] Gebreyesus T, Borgemeister C, Herrero- Jáuregui C, Kelboro G. Transforming urban air quality: green infrastructure strategies for the urban centers of Ethiopia. EnvironPollut 2024;363. https://doi.org/10.1016/j.envpol.2024.125244.

[12] Getnet D, Mekonnen Z, Anjulo A. The potential of traditional agroforestry practices as nature-based carbon sinks in Ethiopia. Nature-Based Solut 2023;4:100079. https://doi.org/10.1016/j.nbsj.2023.100079.

[13] Gill SE, Handley JF, Ennos AR, Pauleit S. Adapting cities for climate change: the role of the green infrastructure. Built Environ 2007;33(1):115–33. https://doi.org/10.2148/benv.33.1.115.

[14] Guo Y, Han J, Bao H, Wu Y, Shen L, Xu X, et al. A systematic analysis and review of soil organic carbon stocks in urban greenspaces. In: *Science of the Total Environment*. Elsevier B.V; 2024. https://doi.org/10.1016/j.scitotenv.2024.174788.

[15] Hairiah K, Dewi S, Agus F, Velarde S, Ekadinata A, Rahayu S, et al. *Measuring Carbon stocks across Land Use Systems: Amanual.* World Agroforestry Centre (ICRAF); 2010.

[16] Hawassa City Administration. (2017). Socio-economic profile of Hawassa. Finance & Economic Development Department, Socio-Economic and Geo-Spatial Data Analysis & Dissemination Core Work Process, Hawassa, Ethiopia.

[17] Herslund L, Backhaus A, Fryd O, Jørgensen G, Jensen MB, Limbumba TM, et al. Conditions and opportunities for green infrastructure – Aiming for green, water-resilient cities in Addis Ababa and Dar es Salaam. Landsc Urban Plan 2018;180:319–27. https://doi.org/10.1016/j.landurbplan.2016.10.008.

[18] Hirabayashi, S., Kroll, C. N., & Nowak, D. J. (2012). *i-Tree Eco Dry Deposition Model Descriptions*. http://www.itreetools.org/eco/resources/iTree_Eco_Dry_Deposition_Model_Descriptions.pdf.

[19] Hirabayashi, S., Kroll, C. N., & Nowak, D. J. (2015). *i-Tree Eco Dry Deposition Model Descriptions*.

[20] IPCC. (2006). Intergovernmental panel on climate change guidelines for national greenhouse gas inventories. Prepared by the national greenhouse gas inventories programme. In: Eggleston HS, Buendia L, Miwa K, Ngara T, Tanabe K (eds). Institute for Global Environmental Strategies.

[21] Ismayilova I, Timpf S. Classifying Urban Green Spaces using a combined Sentinel-2 and Random Forest approach. AGILE: GIScience Series 2022;3:1–6. https://doi.org/10.5194/agile-giss-3-38-2022.

[22] i-Tree Eco. (2020a). i-Tree Eco Guide to International Projects. Washington, D.C., United States: U.S. Forest Service. Retrieved from https://www.itreetools.org/tools/i-tree-eco.

[23] i-Tree Eco. (2020b). *i-Tree. i-Tree Eco user manual. v6, the United States Department of Agriculture and Forest Service.* https://www.itreetools.org/documents/134/i-Tree_Eco_Manual_v6.pdf.

[24] Jovanović D, Kostadinović D, Živković P, Ranđelović D. *Green living Roofs as a Part of Green Infrastructure. International Conference on Urban Planning.* 2020.

[25] Kim J, Kang Y, Kim D, Son S, Kim EJ. Carbon Storage and sequestration analysis by urban park grid using i-tree eco and drone-based modelling. Forests 2024;15(4). https://doi.org/10.3390/f15040683.

[26] Koricho HH, Seboka AD, Fufa F, Gebreyesus T, Song S. Study on the ecosystem services of urban forests: implications for climate change mitigation in the case of Adama City of Oromiya Regional Sate. Ethiopia Urban Ecosystems 2021. https://doi.org/10.1007/s11252-021-01152-0. 0123456789.

[27] Lwasa, S., Seto, K. C., Bai, X., Blanco, H., Gurney, K. R., Kılkış, Ş., Lucon, O., Murakami, J., Pan, J., Sharifi, A., & Yamagata, Y. (2023). *Urban systems and other settlements. In IPCC, 2022: Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the IPCC [P.R. Shukla, J. Skea, R. Slade, A. Al Khourdajie, R. van Diemen, D. McCollum, M. Pathak, S. Some, P. Vyas, R. Fradera, M. Belkacemi, A. Hasija, G. Lisboa, S. Luz, J. Malley, (eds.)]. Cambridge University Press, Cambridge, UK and New York, NY, USA.* (pp. 861–952). Cambridge University Press. DOI: 10.1017/9781009157926.010.

[28] Ma J, Li X, Baoquan J, Liu X, Li T, Zhang W, et al. Spatial variation analysis of urban forest vegetation carbon storage and sequestration in built-up areas of Beijing based on i-tree Eco and Kriging. Urban Forest. Urban Green/ 2021;66. https://doi.org/10.1016/j.ufug.2021.127413.

[29] McPherson, E. G., Nowak, D. J., & Rowan, A. R. (1994). *Chicago's urban forest ecosystem: results of the Chicago Urban Forest Climate Project. Gen. Tech. Rep. NE-186. Radnor, PA: U.S. Department of Agriculture, Forest Service, Northeastern Forest Experiment Station: 201 p*.

[30] McPherson EG, Simpson JR. Carbon Dioxide Reduction through Urban Forestry: Guidelines for Professional and Volunteer tree Planters. *Pacific Southwest Research Station.* 1999.

[31] McPherson EG, Xiao Q, Aguaron E. A new approach to quantify and map carbon stored, sequestered and emissions avoided by urban forests. Landscape Urban Plan 2013;120:70–84. https://doi.org/10.1016/j.landurbplan.2013.08.005.

[32] Minister of Planning and Development (MPD). (2022). *Ethiopia's Third National Communication to the United Nations Framework Convention on Climate Change (UNFCCC). Minister of Planning and Development, Federal Democratic Republic of Ethiopia. Addis Ababa, Ethiopia*.

[33] Muluneh MG, Worku BB. Contributions of urban green spaces for climate change mitigation and biodiversity conservation in Dessie city. Northeastern Ethiopia Urban Climate 2022;46. https://doi.org/10.1016/j.uclim.2022.101294.

[34] Nero BF, Callo-Concha D, Anning A, Denich M. Urban green spaces enhance climate change mitigation in cities of the global South: the case of Kumasi, Ghana. Procedia Eng 2017;198:69–83. https://doi.org/10.1016/j.proeng.2017.07.074.

[35] Nowak. D. J. (1994). Air pollution removal by Chicago's urban forest. In: McPherson, E.G., Nowak, D.J., Rowntree, R.A. (Eds.), Chicago's Urban Forest Ecosystem.

[36] Nowak, D. J. (2020). *Understanding i-Tree : Summary of Programs and Methods* (Issue November). USDA Forest Service General Technical Report N E- 1 86. Radnor. DOI: 10.2737/NRS-GTR-200.

[37] Nowak DJ, Crane DE. Carbon storage and sequestration by urban trees in the USA. Environ Pollut 2002;116:381–9.

[38] Nowak DJ, Crane DE, Stevens JC, Hoehn RE, Walton JT, Bond J. A ground-based method of assessing urban forest structure and ecosystem services. Arboricul Urban Forest 2008;34(6):347–58.

[39] Nowak, D. J., Crane, D. E., Stevens, J. C., & Ibarra, M. (2002). *Brooklyn's Urban Forest. USDA Forest Service, Northeastern Research Station. Published March 2002. USDA Forest Service.* http://www.fs.fed.us/ne.

[40] Nowak DJ, Greenfield EJ, Hoehn RE, Lapoint E. Carbon storage and sequestration by trees in urban and community areas of the United States. Environ Pollut 2013;178:229–36. https://doi.org/10.1016/j.envpol.2013.03.019.

[41] Pearson, T., Walker, S., & Brown, S. (2005). *Sourcebook for Land Use, Land-Use Change and Forestry Projects. With input from Bernhard Schlamadinger, Igino Emmer, (Samalca, K.I., Gier, D.L. and Ali Hussin. (2009). Estimation of tropical forest biomass for assessment of carbon Science Basis.*

[42] Pregitzer CC, Hanna C, Charlop-Powers S, Bradford MA. Estimating carbon storage in urban forests of New York City. Urban Ecosyst 2022;25(2):617–31. https://doi.org/10.1007/s11252-021-01173-9.

[43] Rachid L, Elmostafa A, Mehdi M, Hassan R. Assessing carbon storage and sequestration benefits of urban greening in Nador City, Morocco, utilizing GIS and the InVEST model. Sustain Futures 2024;7. https://doi.org/10.1016/j.sftr.2024.100171.

[44] Rosenzweig C., Solecki, W., Romero-Lankao, P., Mehrotra, S., Dhakal, S., Bowman, T., & Ibrahim., S. A. (2015). *ARC3.2 Summary for City Leaders. Urban Climate*

Change Research Network. Columbia University. New York. Center for Climate Systems Research, Earth Institute, Columbia University.

[45] Sani Haji, Tibebu Assefa, & Rose Bailey. (2020). Addis Ababa City 2016 Greenhouse Gas Emissions Inventory Report (Version 8.0). Addis Ababa City Administration & C40 Cities Climate Leadership Group. Addis Ababa, Ethiopia.

[46] Scott R, Ross I, Hawkins PM. *Fecal sludge management: diagnostics for service delivery in urban areas - report of FSM study in Hawassa, Ethiopia (English)*. Washington, D.C.: World Bank Group. Finance & Economic Development Department; 2016.

[47] Strohbach MW, Arnold E, Haase D. The carbon footprint of urban green space-a life cycle approach. Landscape Urban Plan 2012;104(2):220–9. https://doi.org/10.1016/j.landurbplan.2011.10.013.

[48] Strohbach MW, Haase D. Above-ground carbon storage by urban trees in Leipzig, GERMANY: Analysis of patterns in a European city. Landscape Urban Plan 2012; 104(1):95–104. https://doi.org/10.1016/j.landurbplan.2011.10.001.

[49] Sun Y, Xie S, Zhao S. Valuing urban green spaces in mitigating climate change: a city-wide estimate of aboveground carbon stored in urban green spaces of China's Capital. Glob Chang Biol 2019;25(5):1717–32. https://doi.org/10.1111/gcb.14566.

[50] Tessema MW, Abebe BG, Bantider A. Physical and socioeconomic driving forces of land use and land cover changes: the case of Hawassa City. Ethiopia Front Environ Sci 2024;12. https://doi.org/10.3389/fenvs.2024.1203529.

[51] Tietjen B, Jacobsen K, Hollander J. Climate change and urban migration in sub-Saharan African Cities: IMPACTS and Governance challenges. J Climate Resilience Climate Justice 2023;1:20–32. https://doi.org/10.1162/crcj_a.

[52] Tol RSJ. A social cost of carbon for (almost) every country. Energy Econ 2019;83: 555–66. https://doi.org/10.1016/j.eneco.2019.07.006.

[53] Tulu TT, Mekuria A, Zewdu E. Estimation of Carbon Stock in Church Forests: Implications for Managing Church Forest to help with Carbon Emission Reduction. In: Leal Filho W, Mannke F, Mohee R, Schulte V, editors. *Climate-Smart Technologies, Climate Change Management*. Springer-Verlag; 2013. p. 403–14.

[54] UN-Habitat. (2022). Urban planning law for climate-smart cities: Urban law module. Nairobi, Kenya: UN-Habitat. Retrieved from www.unhabitat.org. www.unhabitat.orgHSNumber:HS/018/22E.

[55] Walker B, Salt D. *Resilience Thinking: Sustaining Ecosystems and people in a changing World*. Washington, DC: Island Press; 2006.

[56] Walkley A, I A B. An examination of the Degtjareff method for determining soil organic matter, and a proposed modification of the chromic acid titration method. Soil Sci 1934;37(1):29–38.

[57] Wang J, Manning DAC, Werner D. The limited potential of soil and vegetation in urban greenspace for nature-based offsetting of institutional carbon emissions. Soil Use Manag 2024;40(2). https://doi.org/10.1111/sum.13081.

[58] White, R., Turpie, J., & Letley, G. (2017). *"Greening Africa's Cities: Enhancing The relationship between urbanization, environmental assets and ecosystem services." World Bank, Washington, DC. License: Creative Commons Attribution CC BY 3.0*. www.wearezephyr.com.

[59] Woldegerima T, Yeshitela K, Lindley S. Ecosystem services assessment of the urban forests of Addis Ababa. Ethiopia Urban Ecosyst 2017;20(3):683–99. https://doi.org/10.1007/s11252-016-0624-3.

[60] World Bank. (2023). The BioCarbon Fund Initiative for Sustainable Forest Landscapes (ISFL) Annual Report.

[61] Yao Y, Wang Y, Ni Z, Chen S, Xia B. Improving air quality in Guangzhou with urban green infrastructure planning: an i-tree Eco model study. J Clean Prod 2022;369. https://doi.org/10.1016/j.jclepro.2022.133372.

[62] Yona Y, Matewos T, Sime G. Analysis of rainfall and temperature variabilities in Sidama regional state. Ethiopia Heliyon 2024;10(7). https://doi.org/10.1016/j.heliyon.2024.e28184.

[63] Yoon TK, Seo KW, Park GS, Son YM, Son Y. Surface soil carbon storage in urban green spaces in three major South Korean cities. Forests 2016;7(6). https://doi.org/10.3390/f7060115.