EEET ECOLOGICAL ENGINEERING & ENVIRONMENTAL TECHNOLOGY

Ecological Engineering & Environmental Technology, 2025, 26(10), 329–342
https://doi.org/10.12912/27197050/211402
ISSN 2719–7050, License CC-BY 4.0

Received: 2025.09.02
Accepted: 2025.09.26
Published: 2025.10.01

Proximity-based spatial assessment of campus carbon balance in the tropics: Developing and testing tree-building distance scenarios

Sri Ngabekti[1*], Dewi Liesnoor Setyowati[2], Trida Ridho Fariz[1], Maulana Malik Wicaksono[1]

[1] Faculty of Mathematics and Natural Sciences, Universitas Negeri Semarang, 50229, Indonesia
[2] Faculty of Social Sciences and Political Science, Universitas Negeri Semarang, 50229, Indonesia
* Corresponding author's e-mail: sri.ngabekti@mail.unnes.ac.id

ABSTRACT

Climate change, biodiversity loss, and pollution constitute the triple planetary crisis, which calls for site-based mitigation actions including those at university campuses. This study introduces a spatial "tree proximity scenario" approach to assess the carbon balance of Universitas Negeri Semarang, Indonesia. The analysis focused on the integrating tree carbon sequestration around buildings with electricity emissions. Emissions were calculated from an inventory of electrical equipment and electricity consumption (baseline) multiplied by the Indonesian grid emission factor (0.844 kgCO_2e/kWh). Sequestration was estimated from a tree inventory (DBH ≥10 cm) using tropical allometric equations, with biomass converted to carbon (0.5) and carbon to CO_2e (3.67). Each tree was mapped relative to building footprints derived from UAV imagery and classified into distance rings: <5 m, 5–10 m, and 10–15 m. Results indicate annual electricity emissions of 526.81 tCO_2e. Annual vegetation sequestration reached 1,230.09 tCO_2e (all trees), with proximity-based scenarios yielding 378.45 (<5 m), 725.18 (≤10 m), and 971.65 tCO_2e (≤15 m). The ≤10 m zone already offsets electricity emissions by 137.65%, while the ≤15 m zone provides substantial surplus sequestration (184.44%), highlighting the dual role of trees as direct carbon sinks and indirect emission reducers through microclimate regulation. These findings underscore the relevance of prioritizing tree protection and planting within 10–15 m corridors around building masses as an effective and replicable mitigation strategy for tropical suburban campuses, aligned with the Net Zero Emission 2060 agenda.

Keywords: campus carbon balance, campus energy consumption spatially, Net Zero Emission, spatial proximity of trees, tree carbon absorption, tropical campus sustainability

INTRODUCTION

Climate change is part of the triple planetary crisis, together with biodiversity loss and environmental pollution. The UNEP report shows that global greenhouse gas (GHG) emissions have doubled from 28.7 to 57.1 GtCO_2eq between 1970 and 2023 (UNEP, 2024). The main contributors are the energy, transportation, industry, buildings, and AFOLU (agriculture, forestry, and other land use) sectors (Filonchyk et al., 2024; Heriyanti et al., 2022; Verma et al., 2023). Globally, the building and construction sector accounts for approximately 21% of total GHG emissions, including university facilities such as classrooms, laboratories, offices, canteens, and dormitories (Cabeza, 2025; Fan et al., 2025; Yang et al., 2025). Higher education institutions with high energy consumption are therefore recognized as significant contributors to CO_2 emissions (Genta et al., 2022; Khoshbakht et al., 2018; Paredes-Canencio et al., 2024). At the same time, universities also hold substantial potential to serve as living laboratories for emission mitigation through energy management and vegetation strategies (Abdullah et al., 2019; Lozano et al., 2019).

At the global level, higher education is increasingly acknowledged as a key actor in achieving the Paris Agreement targets and the Sustainable Development Goals (SDGs). Universities not only contribute substantially to emissions but also possess research capacity, innovation, and practical implementation that can be replicated internationally (Aghamolaei & Fallahpour, 2023). With growing global pressure to reduce emissions by 45% by 2030 (Lee et al., 2023), studies on campus-based mitigation strategies have become crucial in the energy transition and sustainable development agenda. As part of Indonesia's commitment to Net Zero Emission 2060, universities are encouraged to reduce their carbon footprint through energy efficiency and conservation strategies (Kementerian Lingkungan Hidup dan Kehutanan, 2024; Sabran, 2024). One of the most important campus assets is vegetation, particularly trees, which act both as carbon sinks and as key supporters of local environmental quality (Grossi et al., 2023; Zheng et al., 2021). However, most research on campus vegetation still emphasizes total tree carbon stock without considering the spatial proximity of trees to buildings, even though distance strongly influences ecosystem services such as carbon uptake and energy regulation (Czekajlo et al., 2023; Hwang et al., 2015; Setyowati et al., 2024). Scientifically, tree carbon sequestration does not depend on proximity to a specific emission source, since atmospheric CO_2 rapidly mixes on local to global scales and trees absorb carbon from the general atmospheric pool rather than directly from a nearby smokestack or emission point (Domke et al., 2020; Murphy, 2024). Nevertheless, the spatial proximity of trees to buildings may affect their indirect role in carbon mitigation, for instance through shading and microclimate regulation. Hence, developing and testing distance-based analysis in a tropical campus context is essential to understand the spatial distribution of vegetation in shaping campus carbon balance.

On the other hand, several studies have shown that 60–90% of campus carbon emissions are derived from electricity use and building heating, making them the dominant sources, particularly in facilities with high occupant density and significant cooling or seasonal heating needs (Fan et al., 2025; Li et al., 2025; Qi et al., 2025). Electricity consumption alone has been reported to account for up to 78% of total university emissions, exceeding transportation (74%) and fuel use (64%) (Paredes-Canencio et al., 2024). This highlights the critical importance of conducting carbon balance studies within campuses. In the context of tropical countries such as Indonesia, carbon balance studies are especially significant since the tropical climate supports high tree biomass productivity, allowing campuses to possess greater carbon sequestration capacity compared to temperate regions (Castillo-Figueroa, 2021). Moreover, the hot–humid conditions of tropical regions make university buildings highly dependent on cooling, meaning that vegetation surrounding buildings plays a dual role: directly sequestering carbon and reducing cooling demand (Ain et al., 2025; Hwang et al., 2015; Loh et al., 2025; Wang et al., 2015). Thus, tropical campuses are not only sources of emissions but also important providers of ecosystem services relevant to site-based mitigation strategies.

Nevertheless, most carbon balance studies in universities remain limited to conventional approaches, which merely estimate the carbon footprint and subtract it from aggregated vegetation sequestration, both globally (Alelweet, 2025; Kiehle et al., 2023; Rocha et al., 2023) and in Indonesia (Ngabekti & Sultan, 2024; Setyowati et al., 2024). Such approaches restrict our understanding of how spatial factors, particularly tree–building distance, may influence the assessment of carbon balance (Ghosh et al., 2022; Issa et al., 2020). Accordingly, a notable research gap exists regarding distance-based carbon balance analysis. This study aims to develop and test a spatial scenario approach that classifies tree–building proximity to (i) quantify direct carbon sequestration (AGB-based) and (ii) test its adequacy to offset electricity-related emissions in a tropical campus. In contrast to conventional aggregate vegetation offsets, this research introduces distance-band scenarios ($\leq$5 m, $\leq$10 m, $\leq$15 m) as a novel operational planning lens for campus mitigation. The scientific contribution lies in identifying whether proximity-based tree distributions provide sufficient sequestration to achieve net-zero electricity emissions at the campus scale. Our hypotheses are that the $\leq$10 m buffer zone consolidates a majority of the sequestration potential sufficient to neutralize Scope 2 electricity emissions, and extending to a $\leq$15 m corridor provides a critical buffer that enhances resilience against seasonal variability and the loss of large individuals. By testing these hypotheses, the study seeks to advance methodological frameworks for carbon balance analysis and to establish practical, site-specific strategies for emission mitigation in tropical university campuses and similar urban environments.

METHODOLOGY

Study area

This study aimed to quantify the carbon balance at Universitas Negeri Semarang, Indonesia (Figure 1). The key study area was the Faculty of Mathematics and Natural Sciences (FMIPA), selected because it represents the unit with the largest proportion of green open space within the university (Setyowati et al., 2024). Geographically, this area is located between 7°2′58.16″ S – 7°3′ 5.06″ S and 110°23′35.01″ E – 110°23′40.72″ E. FMIPA consists of twelve three-story buildings serving various functions including classrooms, laboratories, administration, and offices. Each building has a different electricity consumption profile, while the surrounding area contains green spaces with diverse tree species. These characteristics make FMIPA a representative case of an educational complex with both high energy intensity and substantial carbon sequestration potential from campus vegetation (Grossi et al., 2023; Khoshbakht et al., 2018).

The analysis compared carbon emissions from building electricity consumption with biological carbon sequestration by trees. Emissions were calculated based on existing electricity consumption (baseline), while tree sequestration was estimated through tree inventory and biomass calculation using allometric equations. Spatial proximity analysis was applied not to assume that trees near buildings directly absorb emissions from the buildings, but to represent the distribution of vegetation carbon stock relative to building footprints and its potential ecosystem benefits. The scope of the study was limited to electricity-related emissions and aboveground biomass. Consequently, indirect benefits such as energy savings from shading, changes in soil carbon stock, or contributions from other forms of green infrastructure were not included in the analysis.

Data and sources

Primary data included an inventory of electronic appliances within the buildings, building floor areas, room usage schedules, and measurements of tree diameter at breast height (DBH). Secondary

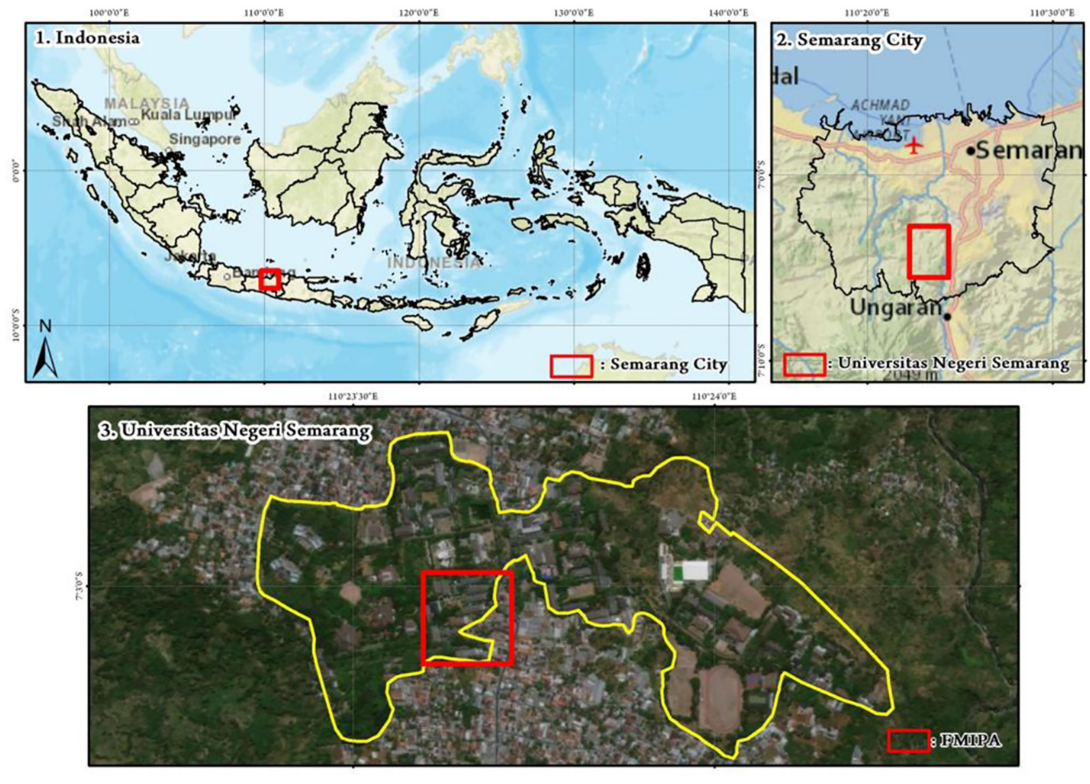

Figure 1. Location study

data comprised the national grid emission factor from Directorate General of Electricity of Indonesia, wood density values from literature databases, and administrative records from the faculty.

Carbon emissions from electricity consumption

An inventory of electronic appliances was conducted in rooms with high usage intensity, such as classrooms, laboratories, administration spaces, lecturers' offices, and the library. For each unit, type, rated power (W), quantity, and duration of use (hours) were recorded. Electricity consumption was calculated as:

$$Etotal \text{ kWh} = \Sigma i \,(Pi / 1000 \cdot ti) \tag{1}$$

where: Pi = rated power of device i (W), ti = operating time of device i (hours).

Carbon emissions were then calculated by multiplying electricity consumption (kWh) with the national grid emission factor:

$$Emissions \text{ kgCO}_2\text{e} = Etotal \text{ kWh} \cdot FEgrid \tag{2}$$

The emission factor (0.844 $kgCO_2e/kWh$) was selected because it is the most recent official dataset available for the Java–Bali grid system (Huzaifi et al., 2020). To test robustness, sensitivity analysis was performed by varying the emission factor by ±10–20%. Results were presented per building and aggregated at the FMIPA level.

Carbon sequestration by trees

All trees with DBH ≥10 cm within the FMIPA area were measured and identified by species. DBH data were used to calculate aboveground biomass (AGB) using the tropical allometric equation of Chave et al. (2005):

$$AGB \text{ (kg)} = \rho \times \exp(-1.499+2.148\ln(\text{DBH})+0.207(\ln(\text{DBH}))^2-0.0281(\ln(\text{DBH}))^3) \tag{2}$$

where: ρ is wood density (g/cm^3) obtained from the Global Wood Density Database (Zanne, 2009), AGB was converted to carbon stock using a carbon fraction of 0.50, following tropical biomass studies (Basuki et al., 2009; Biswas et al., 2021).

The choice of 0.50 was made for consistency with numerous Indonesian and Southeast Asian applications where empirical assessments of tropical tree species indicate that approximately 50% of oven-dry biomass consists of carbon. Using this fraction also facilitates comparability with prior studies on campus vegetation carbon stock. Carbon stock was further converted to CO_2 equivalent using 3.667, the molecular weight ratio of CO_2 (44) to C (12) (Eggleston et al., 2006).

Each tree was mapped relative to building footprints derived from unmanned aerial vehicle (UAV) imagery. UAV imagery was chosen for its very high spatial resolution, which is highly suitable for building footprint digitization (Ahmed et al., 2025; Fariz et al., 2023).To avoid double-counting, each tree was assigned to the nearest distance buffer from the union of all building footprints. Spatial analysis was then performed using buffer rings with radii of <5 m, 5–10 m, and 10–15 m. The choice of these distances follows Hwang et al. (2015) and recent tropical urban tree studies, which show shading and cooling effects are strongest within 5–10 m and decline beyond 15 m. Within this framework, sequestration was analyzed in four scenarios: scenario 1 included all trees in FMIPA, scenario 2 included trees <5 m, scenario 3 included trees 5–10 m, and scenario 4 included trees 10–15 m.

Carbon balance

Carbon balance was calculated by subtracting tree sequestration from building electricity emissions:

$$Carbon\ balance = Total\ \text{CO}_2\text{e}\ emissions - Total\ \text{CO}_2\text{e}\ sequestration \tag{3}$$

Results were expressed in $kgCO_2e$ per year at the building level and for the entire faculty. A negative carbon balance indicates that sequestration exceeds electricity emissions, while a positive balance indicates residual net emissions.

Assumptions and limitations

The methodology was limited to electricity emissions (Scope 2, baseline condition) and aboveground tree carbon sequestration. Belowground biomass, soil organic carbon, and indirect benefits such as shading-induced energy savings were excluded, so estimates are conservative. The emission factor applied referred to the official Indonesian data of 2018, and sequestration estimates depended on DBH, species, and wood density variability. Due to the close spacing of FMIPA buildings (≈5 m), ambiguity arose in attributing trees to specific buildings. Therefore, carbon balance calculations were reported at the aggregate FMIPA level rather than per building. Uncertainty analysis was conducted by varying the emission factor ±10–20, to ensure that results logically followed from the methods.

RESULTS AND DISCUSSION

Electricity consumption and carbon emissions

Faculty of Mathematics and Natural Sciences of Universitas Negeri Semarang comprises twelve operational buildings that support twenty-one study programs spanning mathematics, natural sciences, computer science, and environmental science. This context matters because building functions, namely laboratories, lecture rooms, academic offices, and administration, directly shape distinct daily energy-demand profiles.

Based on field observations, total electricity consumption reached 62,417.30 kWh per month with an average of 5,487.43 kWh per building. Building D-11 exhibited the highest monthly consumption at 9,894.97 kWh per month (Figure 2). This is expected because D-11 hosts genetics and molecular biology laboratories as well as a plant tissue culture laboratory. By contrast, Building D-2 recorded the lowest monthly consumption since it is primarily used for teaching activities.

By function, laboratory buildings are the largest contributors to campus electricity demand, followed by lecturers' offices and administration, while classroom buildings are the lowest (Figure 3). This pattern is consistent with cross-country evidence that identifies laboratories and research spaces as campus energy hotspots due to high densities of electrical equipment, ventilation requirements, and cooling needs that exceed those of classrooms (Bastida-Molina et al., 2022; Khoshbakht et al., 2018). In the study month, laboratories accounted for 44.3 percent of consumption, lecture rooms for 17.5 percent, administration for 9.4 percent, and lecturers' offices for 28.7 percent (Figure 3). These shares reflect equipment-intensive activities in laboratory domains.

Using a grid emission factor of 0.844 $kgCO_2e$ per kWh which is in accordance with the Directorate General of Electricity of Indonesia (Huzaifi et al., 2020), annual electricity-related emissions at FMIPA are estimated at 526.81 tCO_2e per year. This value is higher than a prior study at the same location by Ngabekti and Sultan (2024), which reported 364.95 tCO_2e per year. The increase indicates greater activity intensity and longer operating hours, especially in laboratory buildings. The emission distribution mirrors consumption as laboratories contribute the largest share and classroom buildings the smallest (Figure 4). This finding aligns with Herth & Blok, (2023) and Li et al. (2025), who identified laboratories and libraries as dominant sources of electricity-related emissions in university settings.

Detailed equipment-level inventories reinforce these patterns. Building D11, which functions as a core biology laboratory cluster,

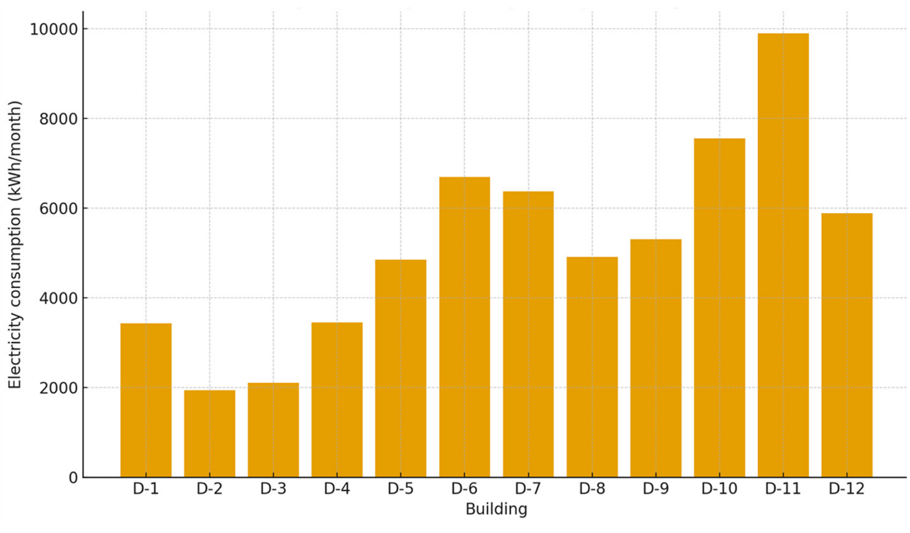

Figure 2. Monthly electricity consumption by building

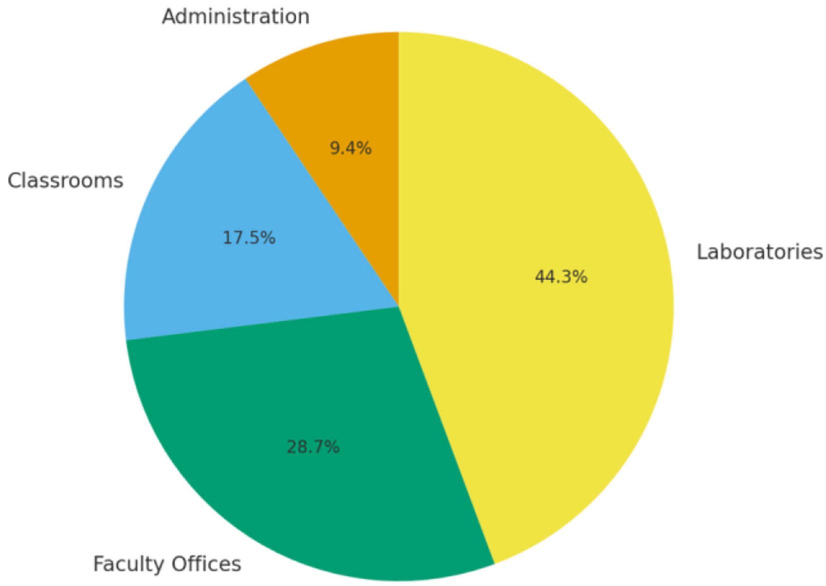

Figure 3. Share of monthly electricity consumption by function

records the highest monthly electricity use at 9,894.98 kWh. Air-conditioning alone contributes 5,372.64 kWh or approximately 54 percent of the total, reflecting the cooling demand of molecular biology and tissue culture laboratories. Building D10, which combines mathematics laboratories and classrooms, reaches 7,552.45 kWh per month. Of this figure, 6,046.92 kWh (around 80 percent) is attributable to air-conditioning, showing how cooling requirements dominate the energy profile. Office-dominated buildings also exhibit similarly high shares of air-conditioning. For example, Building D6 consumes 6,700.61 kWh per month, of which 6,046.56 kWh (about 90 percent) comes from air-conditioning, while Building D12 records 5,886.80 kWh per month with 5,241.60 kWh (roughly 89 percent) from air-conditioning.

By contrast, classroom-oriented buildings consume far less energy. Building D2 records only 1,943.92 kWh per month with around 36 percent from air-conditioning, while Building D3 records 2,108.34 kWh with about 64 percent from air-conditioning. This clear contrast confirms the expectation that building function and the intensity of HVAC systems are the primary drivers of energy demand profiles. At the device level, the dominant contributors are split-type air-conditioning units, typically rated at 1,170 W in both laboratories and offices. Dense arrays of lighting fixtures in teaching and administrative spaces also add significantly to consumption, while computer laboratories, particularly in Building D10, create additional peaks in demand. Together, these factors explain the step-change observed between laboratory or office buildings and general teaching blocks. When the official emission factor of 0.844 $kgCO_2e$ per kWh is applied at the building level, the resulting monthly carbon emissions are directly consistent with the inventory-derived totals. For example, Building D11 produces approximately 8.35 tCO_2e, Building D10 about 6.37 tCO_2e, Building D6 around 5.66 tCO_2e, and Building D12 approximately 4.97 tCO_2e. These values demonstrate that the reported emissions are a logical and reproducible consequence of the recorded electricity use.

To evaluate robustness, we varied the grid emission factor (EF = 0.844 $kgCO_2e/kWh$) by ±10% and ±20%. The implied annual electricity emissions range from ~474.13 to 579.49 tCO_2e (±10%) and from ~421.45 to 632.17 tCO_2e (±20%). In all cases, the ≤10 m and ≤15 m proximity scenarios still offset electricity emissions, indicating that the net-sink conclusion is stable under plausible EF uncertainty. Operational context explains the observed profile. Most FMIPA classrooms still rely on natural ventilation supported by ceiling or standing fans, and teaching uses smart televisions as media alongside whiteboards. Air conditioning in teaching buildings is

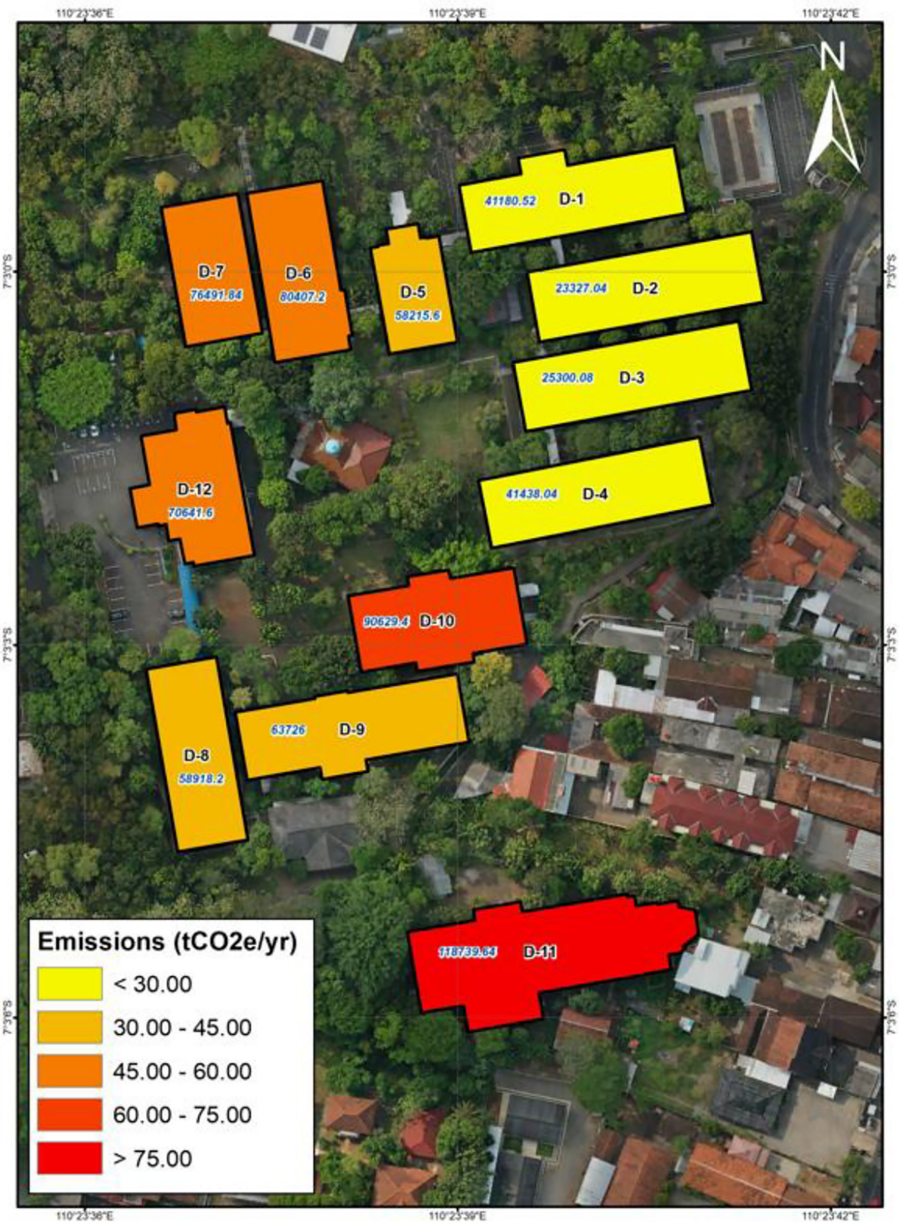

Figure 4. Map of carbon emissions from building electricity use

typically limited to computer laboratories and a subset of practical laboratories, which keeps energy intensity relatively low. Building D-12 functions as both administrative center and leadership suite, which explains its position in the mid to upper consumption group despite not being a laboratory building.

Tree carbon sequestration and carbon balance

The vegetation inventory recorded 356 trees representing 57 species within FMIPA. Spatially, trees are distributed around all buildings within the study area (Figure 5). Total aboveground biomass (AGB) reached 670.35 t, equivalent to a carbon stock of 335.17 t C (Table 1). Converted to sequestration potential, annual uptake is approximately 1,230.09 tCO_2e. Compared with annual electricity emissions of 526.81 tCO_2e, this initial picture indicates substantial sequestration capacity at the campus-district scale.

The species-level summary highlights the dominance of large-canopy taxa. Swietenia mahagoni (91 individuals) constitutes the backbone of the district-scale stock, followed by Mangifera indica (52) and Polyalthia longifolia (40). Mean diameters span from small to very large trees, with examples such as Acacia longifolia (mean DBH ≈ 36.1 cm; mean $\rho \approx$

Figure 5. Tree distribution map and proximity

Table 1. Total sequestration, electricity emissions, and carbon balance by scenario

Scenario	Total sequestration (ton CO_2e/year)	Electricity emissions (ton CO_2e/year)	Carbon balance (ton CO_2e/year)	Offset (%)	Number of trees
1	1230.09	526.81	−537.93	233.5	356
2	378.45	526.81	170.71	71.84	138
3	725.18	526.81	−135.27	137.65	225
4	971.65	526.81	−306.81	184.44	282

0.52 g/cm³) and Adenanthera pavonina (mean DBH ≈ 47.6 cm; mean ρ ≈ 0.70 g/cm³) that contribute disproportionately to AGB. For each individual, AGB was obtained from DBH and species-specific wood density (ρ), carbon stock was computed as C = AGB × 0.50, and CO_2e was derived as CO_2e = C × 3.667. This stepwise transformation (AGB → C → CO_2e) ensures traceability from field measurements to annual sequestration estimates.

Aggregated across FMIPA, the resulting totals are consistent with the inventory: 670.35 t AGB, 335.17 t C (using fC = 0.50), and 1,230.09 tCO_2e per year. At the species level, Swietenia mahagoni contributes ~593.91 tCO_2e (≈48.3% of total), while Mangifera indica and Polyalthia longifolia add ~82.19 tCO_2e (6.7%) and ~81.66 tCO_2e (6.6%), respectively. Large-diameter individuals, such as Ficus altissima, can reach ~44.8 tCO_2e per tree, underscoring the outsized role of keystone trees in the campus carbon balance.

Scenario analysis clarifies the relationship between tree proximity and carbon-balance performance. In Scenario 1, which includes all trees, sequestration reaches 1,230.09 tCO_2e per year and the carbon balance equals −537.93 tCO_2e. Vegetation therefore acts as a net sink that exceeds electricity emissions, corresponding to 233.5 percent offset. When the focus is limited to trees very close to buildings in Scenario 2, that is 0 to 5 m, sequestration decreases to 378.45 tCO_2e and the carbon balance shifts to +170.71 tCO_2e with 71.84 percent offset and 138 trees counted. This indicates a residual deficit.

In Scenario 3, where the proximity band expands from 0 to 5 m to a maximum of 10 m, the number of trees increases from 138 to 225. Sequestration rises from 378.45 to 725.18 tCO_2e per year, an increase of 346.73 tCO_2e that flips the system from a deficit to a net sink at −135.27 tCO_2e with an offset of 137.65 percent. Cumulatively, the ≤10 m radius alone consolidates about 58.95 percent of total sequestration stock referenced to Scenario 1, which can be viewed as an operational proximity threshold that effectively closes electricity emissions for the study year.

In Scenario 4, extending to ≤15 m adds 57 trees for a total of 282. This provides an additional 246.47 tCO_2e, bringing total sequestration to 971.65 tCO_2e per year. The carbon balance strengthens to −306.81 tCO_2e with 184.44 percent offset. In other words, although a net-zero electricity balance is already achieved within ≤10 m, managing vegetation out to ≤15 m supplies a substantial sequestration buffer, approximately 78.99 percent of total stock. This is beneficial for damping seasonal fluctuations in energy use and ecological uncertainties such as the loss of large-diameter individuals due to removal or natural mortality. The results support the argument that corridors within 10 to 15 m around building masses are priority zones for protection and strategic planting without relying on the entire vegetation stock of the district.

Species composition indicates that dominance by specific taxa strongly affects total sequestration. Swietenia mahagoni contributes 593.91 tCO_2e per year, which is 48.33 percent of the FMIPA total. With 91 individuals, S. mahagoni practically forms the backbone of district-scale carbon stock at FMIPA. This dominance is consistent with Lukito & Rohmatiah (2022), who report S. mahagoni as a high-capacity urban CO_2 sink species. Following S. mahagoni, Mangifera indica contributes 82.19 tCO_2e per year, or 6.69 percent, from 52 trees. Polyalthia longifolia contributes 81.66 tCO_2e per year, or 6.64 percent, from 40 trees, and Pterocarpus indicus contributes 56.10 tCO_2e per year, or 4.56 percent, from 13 trees. At the individual scale, Ficus altissima stands out with 44.80 tCO_2e per year from a single tree, illustrating the pivotal role of large-diameter individuals in area-level carbon sequestration.

Proximity distributions confirm that FMIPA's carbon stock is strongly accumulated around building masses. Vegetation within ≤5 m accounts for 30.76 percent of total sequestration in Scenario 1, vegetation within ≤10 m accounts for 58.95 percent, and vegetation within ≤15 m reaches 78.99 percent. This concentration is relevant for planning because it highlights where protection and planting interventions will have the strongest influence on the operational carbon balance.

DISCUSSION

The FMIPA energy-use profile shows laboratories as the main nodes of energy intensity. This results not only from laboratory equipment but

Table 2. Number of trees and total sequestration per proximity

Proximity band	Number of trees	Total sequestration (ton CO_2e/year)	Contribution to Scenario 1 total sequestration (%)
< 5 m	138	378.45	30.76
5–10 m	225	725.18	58.95
10–15 m	282	971.65	78.99

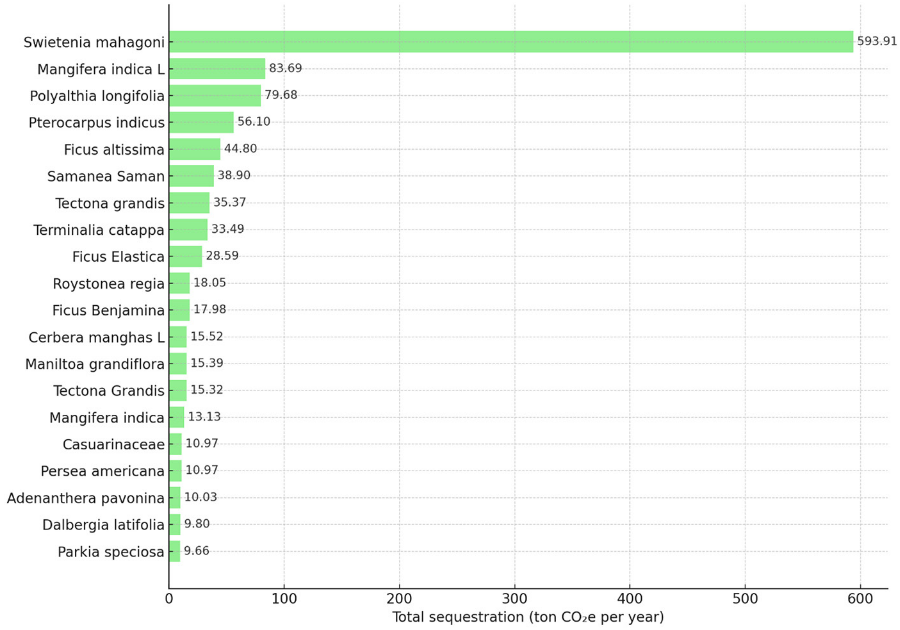

Figure 6. Largest total sequestration by species

also from the need for mechanical cooling and ventilation (Chung-Camargo et al., 2024). The pattern is consistent with Rahmawati et al. (2022), who reported that thermal conditions in Building D-1 exceed comfort thresholds for both temperature and humidity. These conditions necessitate cooling interventions that, in turn, increase electricity consumption. In short, campus energy is expended not only for experiments but also to ensure suitable working and learning environments.

The tree inventory proceeds in a transparent sequence: diameters at breast height (DBH) are converted to aboveground biomass using the selected allometric model; the resulting biomass is then translated into carbon stock by applying the carbon fraction of 0.50; finally, carbon stock is expressed as carbon-dioxide equivalent by multiplying by 3.667. In parallel, the electricity inventory starts from device counts and operating hours to obtain kilowatt-hours, which are then converted to carbon-dioxide equivalent using the grid emission factor. Because both the biological and electrical sides of the balance are built from observed activity data and species-specific wood properties, the proximity-based offsets arise directly from the methodology rather than from undifferentiated aggregate assumptions.

The sensitivity analysis reinforces this conclusion. When the grid emission factor is varied by plus or minus ten to twenty percent, the scenario that includes trees within ten meters of building envelopes continues to offset the annual Scope-2 electricity emissions, and the scenario that extends to fifteen meters preserves a surplus sequestration buffer. Accordingly, the central inference remains stable under plausible parameter uncertainty: trees located within ten to fifteen meters of building masses provide sufficient direct sequestration to neutralize electricity-related emissions, with an additional margin when the wider corridor is considered.

Trees around campus buildings function as both carbon balancers and energy demand suppressors. Large-canopy trees, such as Swietenia mahagoni and Ficus altissima, can lower microclimatic temperatures and reduce cooling loads (Meili et al., 2021; Mohammed et al., 2024). The correlation between tree proximity and emission closure indicates a dual role for vegetation, namely direct carbon sequestration and indirect moderation of energy demand arising from indoor thermal conditions. This supports the argument that mitigation strategies in tropical campuses should integrate energy efficiency with strategic vegetation design rather than treating them as separate tracks.

This study faced several limitations. Energy data are still aggregated, and the lack of building-level sub-metering constrains the clarity of consumption patterns, even though data granularity is essential for precision mitigation design. Campus carbon footprints also extend beyond electricity.

Mobility, construction, and waste management are significant sources that were outside the scope of this analysis. These issues can be addressed by integrating Scope 1, Scope 2, and Scope 3 accounting frameworks. Several university studies show that Scope 3 often constitutes the largest share of campus footprints, reaching 70 to 97 percent, primarily from mobility, construction, and procurement (García-Alaminos et al., 2022; Mendoza-Flores et al., 2019). Without Scope 1–3 integration, campus carbon accounting will be biased and will not reflect the full emission reality (Silva et al., 2023; Valls-Val & Bovea, 2022). An integrated Scope 1–3 framework is therefore needed for comprehensive accounting and for relevance as an instrument to evaluate decarbonization strategies (Mustafa et al., 2022).

Findings at FMIPA open the door for cross-faculty and cross-campus comparisons. Faculties with heavy research profiles are likely to exhibit far more intensive footprints than social sciences or humanities. Such comparisons matter not only for mapping but also for formulating best-practice standards tailored to disciplinary contexts. Integrating thermal comfort, energy efficiency, and vegetation ecology also provides a more realistic picture of sustainability in tropical campuses. This study presents an applicable model for suburban campuses in the tropics that balances energy consumption and vegetation sequestration through a proximity-based approach. The scheme can be replicated to support campus net-zero electricity agendas while improving indoor comfort. Consequently, the study serves not only as a local case but also as a benchmark for higher education institutions in regions with similar climatic and topographic characteristics.

CONCLUSIONS

This study developed and tested a proximity-based spatial approach for a tropical campus by coupling two transparent inventories: a device-hours electricity inventory for Scope-2 emissions and a tree inventory transformed from DBH to AGB to carbon and then to CO_2e using species-level wood density and a 0.50 carbon fraction. Applying this framework at Faculty of Mathematics and Natural Sciences of Universitas Negeri Semarang shows that tree distributions within ≤10 m of building envelopes provide sufficient direct sequestration to fully offset annual electricity-related emissions, while extending management attention to ≤15 m supplies a substantive sequestration buffer that enhances resilience to seasonal demand swings and the potential loss of large trees. A simple uncertainty test that perturbs the grid emission factor by ±10–20% leaves these conclusions unchanged, indicating that the proximity-based offsets are a logical and robust consequence of the measured activity data and the allometric method rather than an artifact of aggregation. Practically, the results support priority protection and planting in the 10–15 m corridors around building masses as a replicable, site-based mitigation strategy for tropical suburban campuses, aligning operational planning with Indonesia's Net Zero Emission 2060 agenda. Methodologically, the present analysis is conservative (Scope-2 focus; aboveground biomass only). Future work should add building sub-metering, integrate Scopes 1–3, and explicitly quantify indirect mitigation effects (e.g., microclimate cooling and reduced HVAC loads) so that proximity scenarios can optimize not only carbon balance but also thermal comfort and energy efficiency at room and building scales.

REFERENCES

1. Abdullah, S., Mansor, A. A., Ahmed, A. N., & ... (2019). Carbon footprint assessment for academic institution: a UI greenmetric approach. *International Journal of Scientific and Technology Research 8,* (11), 1752-1755.
2. Aghamolaei, R., & Fallahpour, M. (2023). Strategies towards reducing carbon emission in university campuses: A comprehensive review of both global and local scales. *Journal of Building Engineering*. https://www.sciencedirect.com/science/article/pii/S2352710223013633
3. Ahmed, S. F., EL-Shazely, A. H., & Ahmed, W. (2025). Deep Learning for Building Footprint Extraction Using UAV-Based Orthoimages. *Journal of the Indian Society of Remote Sensing*, *53*(4), 1243–1262.
4. Ain, O., Khalil, H. B., El-Maraghy, M., & Marzouk, M. (2025). Generative Design and Multi-Objective Optimization for Enhanced Building Thermal Performance. *Case Studies in Thermal Engineering*, 106621.
5. Alelweet, O. (2025). Carbon Footprint Assessment Initiative and Trees Role in Reducing Emissions. *Advances in Environmental and Engineering Research*, *6*(1), 1–5.

6. Bastida-Molina, P., Torres-Navarro, J., Honrubia-Escribano, A., & Gómez-Lázaro, E. (2022). Electricity consumption analysis for university buildings. Empirical approach for University of Castilla-La Mancha, campus Albacete (Spain). *Renewable Energy and Power Quality Journal*, *20*, 216–221.
7. Basuki, T. M., Van Laake, P. E., Skidmore, A. K., & Hussin, Y. A. (2009). Allometric equations for estimating the above-ground biomass in tropical lowland Dipterocarp forests. *Forest Ecology and Management*, *257*(8), 1684–1694.
8. Biswas, S., Biswas, A., Das, A., & Banerjee, S. (2021). Phytosociological assessment and carbon stock estimation and valuation in the tropical dry deciduous forest of Bihar. *Ecofeminism and Climate Change*, *2*(1), 2–16.
9. Cabeza, L. F. (2025). Cost-effective latent thermal energy storage for refurbishment and retrofitting of buildings. In *Cost-Effective Energy-Efficient Methods for Refurbishment and Retrofitting of Buildings* (pp. 23–36). Elsevier.
10. Castillo-Figueroa, D. (2021). Carbon cycle in tropical upland ecosystems: a global review. *Web Ecology*, *21*(2), 109–136.
11. Chave, J., Andalo, C., Brown, S., Cairns, M. A., Chambers, J. Q., Eamus, D., Fölster, H., Fromard, F., Higuchi, N., & Kira, T. (2005). Tree allometry and improved estimation of carbon stocks and balance in tropical forests. *Oecologia*, *145*, 87–99.
12. Chung-Camargo, K., González, J., Chen Austin, M., Carpino, C., Mora, D., & Arcuri, N. (2024). Advances in retrofitting strategies for energy efficiency in tropical climates: a systematic review and analysis. *Buildings*, *14*(6), 1633.
13. Czekajlo, A., Alva, J., Szeto, J., Girling, C., & Kellett, R. (2023). Impact of 2050 tree shading strategies on building cooling demands. *Buildings & Cities*, *4*(1).
14. Domke, G. M., Oswalt, S. N., Walters, B. F., & Morin, R. S. (2020). Tree planting has the potential to increase carbon sequestration capacity of forests in the United States. *Proceedings of the National Academy of Sciences*, *117*(40), 24649–24651.
15. Eggleston, H. S., Buendia, L., Miwa, K., Ngara, T., & Tanabe, K. (2006). *2006 IPCC guidelines for national greenhouse gas inventories*.
16. Fan, F., Zhu, S., Huang, J., Xu, X., & Xu, F. (2025). Life cycle assessment of carbon emissions and reduction potential exploration of new building complexes in Universities: A case study in China. *The International Journal of Life Cycle Assessment*, *30*(4), 621–637.
17. Fariz, T. R., Jatmiko, R. H., Mei, E. T. W., & Lutfiananda, F. (2023). Interpretation on aerial photography for house identification on landslide area at Bompon sub-watershed. *AIP Conference Proceedings*, *2683*(1).
18. Filonchyk, M., Peterson, M. P., Yan, H., Gusev, A., Zhang, L., He, Y., & Yang, S. (2024). Greenhouse gas emissions and reduction strategies for the world's largest greenhouse gas emitters. *Science of The Total Environment*, *944*, 173895.
19. García-Alaminos, Á., Gilles, E., Monsalve, F., & ... (2022). Measuring a university's environmental performance: A standardized proposal for carbon footprint assessment. *Journal of Cleaner Production.* https://www.sciencedirect.com/science/article/pii/S0959652622013956
20. Genta, C., Favaro, S., Sonetti, G., Fracastoro, G. V, & ... (2022). Quantitative assessment of environmental impacts at the urban scale: the ecological footprint of a university campus. *Environment, Development and Sustainability*. https://doi.org/10.1007/s10668-021-01686-5
21. Ghosh, S., Dinda, S., Chatterjee, N. Das, Dutta, S., & Bera, D. (2022). Spatial-explicit carbon emission-sequestration balance estimation and evaluation of emission susceptible zones in an Eastern Himalayan city using Pressure-Sensitivity-Resilience framework: An approach towards achieving low carbon cities. *Journal of Cleaner Production*, *336*, 130417.
22. Grossi, F., Ge, H., Zmeureanu, R., & Baba, F. (2023). Feasibility of planting trees around buildings as a nature-based solution of carbon sequestration—An LCA approach using two case studies. *Buildings*, *13*(1), 41.
23. Heriyanti, A. P., Purwanto, P., Purnaweni, H., & Fariz, T. R. (2022). Greenhouse Gas Emissions and Biogas Potential From Livestock in Rural Indonesia. *Jurnal Pendidikan IPA Indonesia*, *11*(1), 35–46. https://doi.org/10.15294/jpii.v11i1.34465
24. Herth, A., & Blok, K. (2023). Quantifying universities' direct and indirect carbon emissions–the case of Delft University of Technology. *International Journal of Sustainability in Higher Education*, *24*(9), 21–52.
25. Huzaifi, H., Budiyanto, A., & Sirait, J. (2020). *Study on the carbon emission evaluation in a container port based on energy consumption data*.
26. Hwang, W. H., Wiseman, P. E., & Thomas, V. A. (2015). Tree planting configuration influences shade on residential structures in four US cities. *Arboriculture & Urban Forestry (AUF)*, *41*(4), 208–222.
27. Issa, S., Dahy, B., Ksiksi, T., & Saleous, N. (2020). A review of terrestrial carbon assessment methods using geo-spatial technologies with emphasis on arid lands. *Remote Sensing*, *12*(12), 2008.
28. Kementerian Lingkungan Hidup dan Kehutanan. (2024). *Laporan Inventarisasi Gas Rumah Kaca (GRK) dan Monitoring, Pelaporan, Verifikasi (MPV) 2023 [Greenhouse Gas (GHG) Inventory*

and Monitoring, Reporting, and Verification (MPV) Report 2023] (Kementerian Lingkungan Hidup dan Kehutanan. Direktorat Jenderal Pengendalian Perubahan Iklim. Direktorat Inventarisasi GRK dan MPV).

29. Khoshbakht, M., Gou, Z., & Dupre, K. (2018). Energy use characteristics and benchmarking for higher education buildings. *Energy and Buildings*, *164*, 61–76.
30. Kiehle, J., Kopsakangas-Savolainen, M., Hilli, M., & ... (2023). Carbon footprint at institutions of higher education: The case of the University of Oulu. *Journal of Environmental Management*. https://www.sciencedirect.com/science/article/pii/S0301479722026299
31. Lee, H., Calvin, K., Dasgupta, D., Krinner, G., Mukherji, A., Thorne, P., Trisos, C., Romero, J., Aldunce, P., & Barret, K. (2023). *IPCC, 2023: Climate change 2023: Synthesis report, summary for policymakers. Contribution of working groups i, II and III to the sixth assessment report of the intergovernmental panel on climate change [core writing team, h. Lee and j. Romero (eds.)]. IPC*.
32. Li, R., Bai, Z., Ye, C., Ablameyko, S., & Ye, S. (2025). Urban green space vegetation height modeling and intelligent classification based on UAV multispectral and oblique high-resolution images. *Urban Forestry & Urban Greening*. https://www.sciencedirect.com/science/article/pii/S1618866725001190
33. Loh, D. Z. T., Zhang, L., & Zhang, Y. (2025). Dynamic simulation and experimental analysis of vertical greening systems on building energy efficiency. *Energy and Buildings*, *343*, 115925.
34. Lozano, R., Barreiro-Gen, M., Lozano, F. J., & Sammalisto, K. (2019). Teaching sustainability in European higher education institutions: Assessing the connections between competences and pedagogical approaches. *Sustainability*, *11*(6), 1602.
35. Lukito, M., & Rohmatiah, A. (2022). Stored carbon FMU Lawu Manunggal using a biomass approach in the community forest in Sidomulyo Village, Magetan Regency, Indonesia. *Eng Technol J*, *7*(10), 1584–1596.
36. Meili, N., Acero, J. A., Peleg, N., Manoli, G., Burlando, P., & Fatichi, S. (2021). Vegetation cover and plant-trait effects on outdoor thermal comfort in a tropical city. *Building and Environment*, *195*, 107733.
37. Mendoza-Flores, R., Quintero-Ramírez, R., & ... (2019). The carbon footprint of a public university campus in Mexico City. *Carbon Management.* https://doi.org/10.1080/17583004.2019.1642042
38. Mohammed, A., Khan, A., Khan, H. S., & Santamouris, M. (2024). On the cooling energy impacts of combined urban heat mitigation strategies in subtropical urban building environment. *Energy and Buildings*, *309*, 113918.
39. Murphy, D. J. (2024). Carbon sequestration by tropical trees and crops: A case study of oil palm. *Agriculture*, *14*(7), 1133.
40. Mustafa, A., Kazmi, M., Khan, H. R., Qazi, S. A., & Lodi, S. H. (2022). Towards a carbon neutral and sustainable campus: Case study of NED university of engineering and technology. *Sustainability*. https://www.mdpi.com/2071-1050/14/2/794
41. Ngabekti, S., & Sultan, H. (2024). Carbon Footprint Analysis in UNNES Sekaran Campus Environment as Energy Conservation Data. *Indonesian Journal of Earth and Human*. https://journal.unnes.ac.id/journals/ijeh/article/view/12307
42. Paredes-Canencio, K. N., Lasso, A., Castrillon, R., Vidal-Medina, J. R., & Quispe, E. C. (2024). Carbon footprint of higher education institutions. *Environment, Development and Sustainability*, 1–34.
43. Qi, Y., Chen, L., Xu, J., Liu, C., Gao, W., & Miao, S. (2025). Influence of university campus spatial morphology on outdoor thermal environment: a case study from Eastern China. *Energy and Built Environment*. https://www.sciencedirect.com/science/article/pii/S266612332300079X
44. Rahmawati, L. Z. A., Hartanto, T., Pratiwi, A. S., Tiaraningrum, F. H., Zulfani, S. D., Jabbar, A., & Fariz, T. R. (2022). Perbandingan Kualitas Udara Dalam Ruang Gedung D1 Fmipa Berdasarkan Arah Sinar Matahari. *Proceeding Seminar Nasional IPA*, 134–141.
45. Rocha, T. de A., Silva, L. B., Alves, E., & ... (2023). Carbon footprint in an educational institution and compensation potential in urban forests. *Environmental Development.* https://www.sciencedirect.com/science/article/pii/S221146452300060X
46. Sabran, A. (2024). *Gandeng Civitas Kampus, Pemerintah Optimis Target Zero Emission 2060 Tercapai [Partnering with the Campus Community, the Government is Optimistic That the 2060 Zero Emission Target Will Be Achieved]*. https://wartakota.tribunnews.com/2024/06/15/gandeng-civitas-kampus-pemerintah-optimis-target-zero-emission-2060-tercapai?page=all
47. Setyowati, D. L., Hardati, P., Amin, M., & Trihatmoko, E. (2024). Trees spatial distribution and energy awareness to reduce net CO_2 emission at Universitas Negeri Semarang Campus, Indonesia. *Journal of Environmental Science and Management*, *27*(2).
48. Silva, L. A. da, Dutra, A. R. A., Soares, T. C., Birch, R. S., & ... (2023). Trends in research: carbon footprint reduction in universities as a way to achieve a green campus. *International Journal of Sustainability in Higher Education*. https://doi.org/10.1108/IJSHE-10-2021-0440

49. UNEP. (2024). Global Status Report for Buildings and Construction: Beyond Foundations-Mainstreaming Sustainable Solutions to cut Emissions from the Buildings sector [Internet]. *United Nations Environment Programme: Nairobi, Kenya*.
50. Valls-Val, K., & Bovea, M. D. (2022). Carbon footprint assessment tool for universities: CO_2UNV. *Sustainable Production and Consumption*. https://www.sciencedirect.com/science/article/pii/S235255092100333X
51. Verma, K., Sharma, P., Bhardwaj, D. R., Kumar, R., Kumar, N. M., & Singh, A. K. (2023). Land and environmental management through agriculture, forestry and other land use (AFOLU) system. *Land and Environmental Management through Forestry*, 247–271.
52. Wang, Y., Bakker, F., de Groot, R., Wortche, H., & Leemans, R. (2015). Effects of urban trees on local outdoor microclimate: Synthesizing field measurements by numerical modelling. *Urban Ecosystems*, *18*(4), 1305–1331.
53. Yang, C., Yao, T., Shiming, D., & Jiang, W. (2025). Carbon emissions accounting and uncertainty analysis in campus settings: A case study of a university in Sichuan, China. *PloS One*, *20*(4), e0321216.
54. Zanne, A. E. (2009). Global wood density database. *Dryad*.
55. Zheng, N., Li, S., Wang, Y., Huang, Y., Bartoccid, P., & ... (2021). Research on low-carbon campus based on ecological footprint evaluation and machine learning: A case study in China. *Journal of Cleaner Production*. https://www.sciencedirect.com/science/article/pii/S0959652621033679