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A GIS-Based Assessment of Land Cover Changes and Tree Species Suitability for Urban Greening Policies in the City of Kitwe, Zambia

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Abstract

Study objective and design: A change vector analysis (CVA) was used to determine land cover (LC) changes and identify tree species that are best for urban greening based on carbon sequestration and air pollution. The study assessed LC change in Kitwe, Zambia, from 1990 to 2015. This study identified the most planted urban tree species along Kitwe's main roads and highways and evaluated typical urban tree species' pH, RWC, total chlorophyll, ascorbic acid, and biomass.
Place and length of study: The urban trees in Kitwe, Zambia, make up the study population. The city of Kitwe is a thriving centre for mining and commercial activities and is situated in Zambia's Copperbelt Province. The investigation took place during 2018 and 2019.
Methodology: The NDVI and BSI indices were created using spectral indices created from Landsat images of Kitwe taken in 1990 and 2015, respectively. The size and direction of the LC were then determined using CVA, and a district database of land cover changes was constructed using GIS. Urban trees from the built-up area were utilised to create an inventory of common urban tree species based on the land cover classification. The anticipated performance index (API), which measures the suitability of tree species for improving air quality, and the air pollution tolerance index (APTI), which measures the suitability of tree species for urban greening, are two of the three assessment methods that were employed. In addition, above-ground biomass (AGB) was employed to quantify the carbon sequestration contribution of the current urban forest.
Results: The study discovered that between 1990 and 2015, mining activity and urban growth in Kitwe both contributed to changes in the area's LC. While the central business district still exhibits a persistent presence as a result of the town's age, having sprung up before the 1990s with more expansions in the new areas, areas being monitored showed low and medium change intensity, mostly in the northeast of the district. In the current investigation, there was a significant difference in the

relative abundance of species (p = 0.05). In the study site, *Mangifera indica* (RA = 12.3%) and *Delonix regia* (RA = 15.9%) were the two most prevalent species. According to the study, eleven species were found, and each has accumulated carbon in a unique way throughout time depending on its allometry and age. These distinctions in physiological response (tolerance) to air pollution are noteworthy. *Bauhinia variegata*, *Toona ciliate*, *Gmelina arborea*, *Eucalyptus grandis*, and *Delonix regia* were all identified as suitable tree species.
Conclusion: Over the past 25 years, more than 50% of the land cover has changed, with the majority of that change occurring in regions that are now classified as built-up areas. The majority of Kitwe's urban forests are found in the populated areas and are made up of a variety of ornamental trees that are frequently cultivated for their aesthetic value, attractiveness, and shade. According to the research, this mixture also includes opportunistic urban trees (invasive species) and fruit-bearing trees intermingled with native species. Overall, this study suggests the following species: For urban trees suited for greening programmes aimed at improving air quality and providing shade and beauty in green areas, residences, and sidewalks that have a low air pollution environment, consider *Bauhinia variegata*, *Toona ciliate*, *Gmelina arborea*, *Eucalyptus grandis*, and *Delonix regia*.

Keywords: land use, change vector analysis, remote sensing, urban forest management, species list, urban planning, smart cities, air pollution

1. Introduction

By 2050, cities will be home to 66% of the world's population due to the rapid growth of the population [1]. The future of both people and the earth lies in cities. Urban ecosystems are in danger due to population growth and rural-to-urban migration [2]. According to numerous studies [3–7], many tree species are endemic, invasive, or cohabit in urban settings. They make it possible for human cultures to advance socially, economically, and culturally. Most cities are densely populated and frequently have a negative impact on the environment. Increased demand for social services and resources results in resource depletion and a greater carbon footprint.

Pollutants are produced between the urban complex and the natural environment, according to the cyclic nature portrayal and material balance theory [8, 9]. Environmental stress can have an impact on traffic, noise, and air quality [10, 11]. By reducing water recharge and percolation zones, more concrete leads to urban heat islands, heat waves, and a changing global climate [12]. Both mobile and fixed sources of urban air pollution raise global air temperature and carbon dioxide concentration [CO_2] [13]. Environmental pressures are the root cause of climate change. Due to extensive use of fossil fuels for manufacturing, transportation, heating, and other industrial activities, cities are the main source of anthropogenic CO_2 emissions [14, 15]. 90% of the 4.2 million people who died in 2016 from breathing polluted air were city dwellers, according to UN figures [1]. The metropolitan population of the world, which makes up more than 50%, is highly exposed. Evaluations of pollution and the connections between anthropogenic and forest ecosystems focus on urban areas.

Land degradation reduces long-term ecological function [16]. Examples of degradation include formation of unproducive monocultures by invasive species, compaction, erosion, salinization, and desertification. The degradation of the soil and vegetation has an impact on productivity [16, 17]. Concerns regarding the rising need for food, animal feed, and fuel are raised on a worldwide scale as a result. We have been able to pinpoint the locations and mechanisms of degraded lands all across the world thanks to remote sensing data [16]. These methods should map essential aspects that will help urban centres achieve a sustainable future and monitor dynamics that allow historical trends and scenario prediction [18].

Spatial data enables the use of vegetation cover indices to measure land degradation in semi-arid environments, which is difficult due to vegetation growth and changes [5, 19]. Remote sensing relies on channel sensitivity to radiation within narrow wavelength bands because detectors record EMR in numerous bands. By using visible bands 1, 2, and 3, one may locate roads. Bands 4, 5, and 7 of the reflective infrared spectrum can distinguish between land and water. Thermal imaging employs band 6. Using multispectral bands, Jones and Vaughan [20] provide local and regional mapping of vegetation types and conditions. According to Young *et al.* [21], the NIR and SWIR bands are useful for mapping plant and soil moisture, water quality, wetlands, rivers, and coastal environments. Wang *et al.* [22] used thermal infrared bands to map and comprehend wildfire ecology. Anderson *et al.* [23] used them to manage water resources and track evapotranspiration.

Tracking the effects of human activity on the environment can be done through land degradation and cover changes. Applying the outcomes and results involves researching this influence in order to reduce or control the change. Using the red and infrared spectral bands of remote sensing, vegetation indices can be made to distinguish between places with more vegetation than bare soil. It is difficult to evaluate land degradation using vegetation cover indices in semi-arid environments due to vegetation growth and alterations [5]. Remote sensing relies on channel sensitivity to radiation within a specific wavelength range because detectors record EMR at various wavelengths. Yuan *et al.* [19] provide proof of concept, while [24] suggest that more complex techniques have been developed, with insights on detection and a demonstration of how they can be used to classify LC changes for statistical learning as well as temporal information modelling and forecasting. There have been breakthroughs in deep learning using data from remote sensing [25]. This study focuses on image arithmetic-based algorithms that directly compare pixel values from multi-temporal images to create image difference maps, which are then used to categorise pixels into altered or unaltered classes [26]. Methods for detecting changes in time have been broadly classified. In this paper, the basic change vector analysis presented by Yuan *et al.* [19] and Xu *et al.* [27] is employed.

A system's adaptive capacity is defined as its potential to respond to recent or impending climatic change [28, 29]. Urban forests are more capable of adapting to pressures from climate change. The phrase describes procedures that modify a system's reaction to environmental stresses like pollution. According to Butardo and Tenefrancia [30], the institutional, economic, and ecological health of urban areas, as well as their reliance on infrastructure, governance, and natural resources, all affect their capacity for adaptation. Additionally, it asserts that societies with high levels of adaptation are more resilient and able to bounce back from trying situations. As a result, trees can improve urban air quality while reducing air pollution and delivering ecosystem services. Engle [31] claims that the idea is usually overlooked and that one might assess a system's adaptive capacities by fusing knowledge from vulnerability and resilience frameworks. One must first understand how fragile and robust different tree species are in order to fully grasp the urban forest's ability to adapt to air pollution in cities. The use of biochemical parameters in trees can achieve this.

According to Escobedo *et al.* [32, 33], Sahu & Kumar Sahu [34], and Mwaanga *et al.* [35] ambient air pollutants in cities alter the physiological and biochemical characteristics of urban trees. By 2030, local governments are required by SDG 11 to make cities and human settlements more diverse, secure, resilient, and sustainable. Urban forests have been extensively utilised in these towns' urban greening schemes. As a result, these green programmes and campaigns need to have strict selection criteria in order to include more robust urban trees and be more successful. Urban trees that are handy and useful are scarce nonetheless. There are a limited number of screening methods and technical data, such as species lists, decision support tools, databases, and rules for city greening initiatives, in many countries, including Zambia. Mining communities must limit the air pollution caused by mineral prospecting. In order to identify viable tree species for urban greening based on air pollution tolerance, adaptation, and carbon sequestration, urban planners need to use physiological and biochemical data.

Ambient air pollution, among other things, has an impact on the physiological and biochemical characteristics of urban trees [32–35]. Therefore, a strong selection criterion that encourages resilient urban trees at these levels should be given priority in green programmes and campaigns. Numerous African cities have urban greening initiatives in place to increase the amount of urban forest cover, but little is known about how to choose resilient urban trees. Zambia is no exception. The air in mining towns is regularly contaminated by mineral exploration. In Zambia, urbanisation has led to problems with both human and economic expansion and environmental degradation with city dwellers ranking better streets, roads, public transport and mobility, crime prevention and security of tenure, and reliable energy at home and work, which were ranked seventh, eighth and ninth biggest problem, respectively [36]. Simukanga [37] claimed that air pollution in the Copperbelt Province was caused by transportation and mining. Thus, in order to find tree species that can adapt to different environmental conditions and tolerate air pollution, studies that use physiological and biochemical markers are critical to effective urban management.

This experimental study tracks Kitwe's urban forest change using CVA as proposed by Xu *et al.* [27], and it determines which tree species are best for urban greening based on their adaptive capacity, carbon sequestration, and air pollution. The study studied LC change in Kitwe, Zambia, from 1990 to 2015. This study also identified the most planted urban tree species along Kitwe's main roads and highways and evaluated typical urban tree species' pH, RWC, total chlorophyll, ascorbic acid, and biomass. Three assessment methods were used to identify the best assessment criteria and the best tree kind and composition for a region's quality of life, namely APTI and API, which measure a tree's psychological and environmental adaptability [10, 34]. Few studies have examined how two or more tree species reduce urban forest air pollution or linked these indices to carbon sequestration [2]; as such, this is the third assessment tool. Sequential biomass changes can quantify urban tree productivity and carbon fluxes from tree biomass.

2. *Methodology*

2.1. Study area

The study population comprises the urban centre of Kitwe, Zambia. Kitwe district is located between latitudes 12° and 13° east and longitudes 27° and 29° south (Figure 1) in the Copperbelt Province of Zambia. The mean altitude is over 1295 m above sea level, with an annual mean temperature of 22.3 °C and a mean yearly precipitation of 1226 mm. The district has three main seasons: the cold-dry season (April–July), which has a mean temperature of 15 °C. The hot dry season (August–October) has a mean temperature between 18.5 °C and 37 °C.

The city of Kitwe is located inside the biome known as tropical and subtropical grasslands, savannas, and shrublands. Specifically, it is within the Central Zambezian Miombo woodland ecoregion, which covers about half of the country. The Miombo woodland, characterised by the prevalence of Brachystegia, Julbernardia, and Isoberlinia tree species, which belong to the legume family. This places the City as aprt of a vast vegetation formation found in central, eastern, and

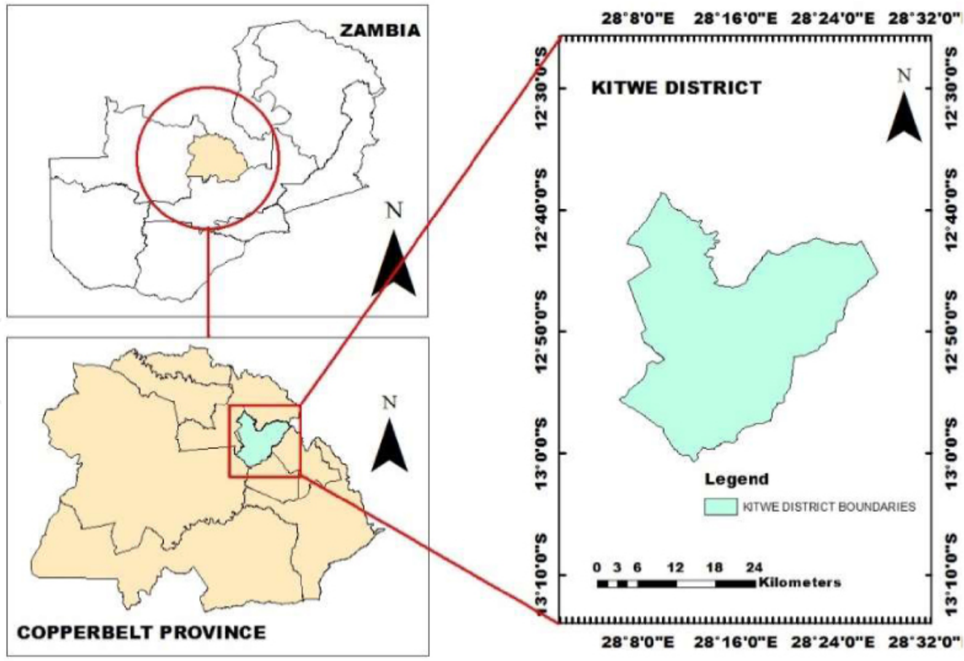

Figure 1. Location of Kitwe.

southern Africa. This ecosystem is known for its seasonal dryness and deciduous nature. The city's charecteristic forested area is characterised by the presence of dambos, which are grassy wetlands that serve as the source and borders of rivers.

The study location is the 'Hub of the Copperbelt' and is more urbanised due to the city's growing importance as an urban centre. It is also a mining town with trade activities. Though the district covers an area of 777 km^2, the urban part of the district is made up of 24 formal settlements and 19 informal settlements with few or no basic municipal services [38]. According to UN studies (2009), poor waste management, poor water supply and sanitation, especially in low-income areas, poor road networks and drainage systems, the growth and expansion of informal settlements and their attendant problems, inadequate public health services, congestion in the Central Business District, particularly in the city market, air pollution from mining operations, and a declining economy were the main environmental development issues in Kitwe. These urban concerns have deteriorated urban living and environmental circumstances, lowering city dwellers' quality of life making the city a good study area.

Kitwe is currently the most populated district in Copperbelt Province and the second most populated district in Zambia, with the present population standing at 522,092 with an estimated 3.3% growth rate per annum [39]. The city has seen major expansions over the past 25 years, with a 72.76% increase in population (from 337,000 to 522,092 people), and this has called for the local authority to instigate regularising and upgrading the informal settlements located in designated residential areas sometime in 2014 [1].

In terms of administration, Kitwe City Council is the supreme decision-making body at the district level. The District Council is responsible for all aspects of city planning and development, and as such, it oversees the formulation of local policies and approves district development plans. The council management structure consists of democratically elected councillors that represent their electorate in the twenty-five (25) wards. As such, this makes Kitwe City Council the primary custodian of urban management in the city.

2.2. Research design

The overall research design followed an exploratory study approach using both qualitative and quantitative methods of data collection and analysis in an integrated manner to meet the intended objectives. An epistemological and deductive approach to building the methods and procedures was used. The design was determined to understand the fundamental issues related to CVA (Figure 2) and the selection process of suitable trees (Figure 3). The initial community analysis was conducted during the rainy season to capture the peak growth of trees in 2018.

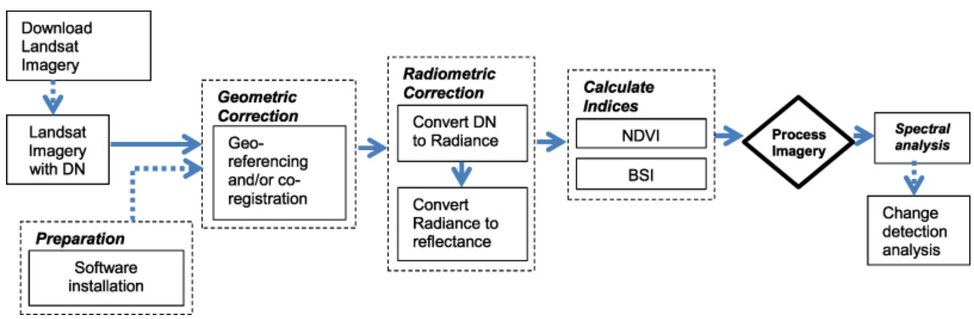

Figure 2. Conceptual framework for conducting vector change analysis.

2.2.1. Remote sensing and GIS methods

The study used Landsat images of Kitwe for two distinct years (1990 and 2015).[1] To undertake preliminary treatment of the images (see Figure 2) and processing, the study used EDRAS IMAGINE 2014 while the mapping was done using ArcGIS 10.4.

[1]Downloaded from the U.S. Geological Survey (USGS) website using EarthExplorer (http://earthexplorer.usgs.gov/)

The Landsat images obtained had the characteristics outlined in Table 1 and were examined for the appropriate bands required for the project.

2.2.1.1. Image preparation and processing The study evaluated datasets consisting of two images from two time points; 1990 and 2015. These two chosen datasets covered a larger period of coverage (i.e., 25 years) to enable the study to follow the significant urban expansion of the city of Kitwe. The Landsat 5 and Landsat 7

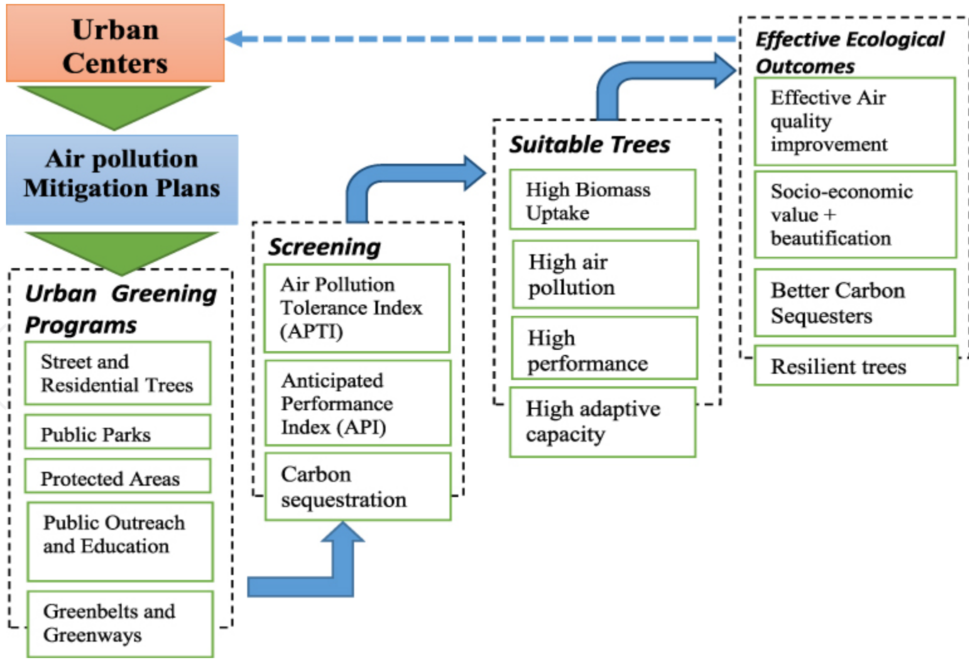

Figure 3. Conceptual framework for identification of urban greening suitable plants.

Enhanced Thematic Mapper Plus (ETM+) sensors with six bands and a spatial resolution of 30 m acquired these two multi-spectral datasets. The dataset consists of two images acquired for the city of Kitwe, Zambia, in November 2017 (T_1 and T_2) with a WGS-84 projection, and the two images are both 400 × 400 pixels. The study focused on showing changes mainly related to city expansion, as shown in Figure 4.

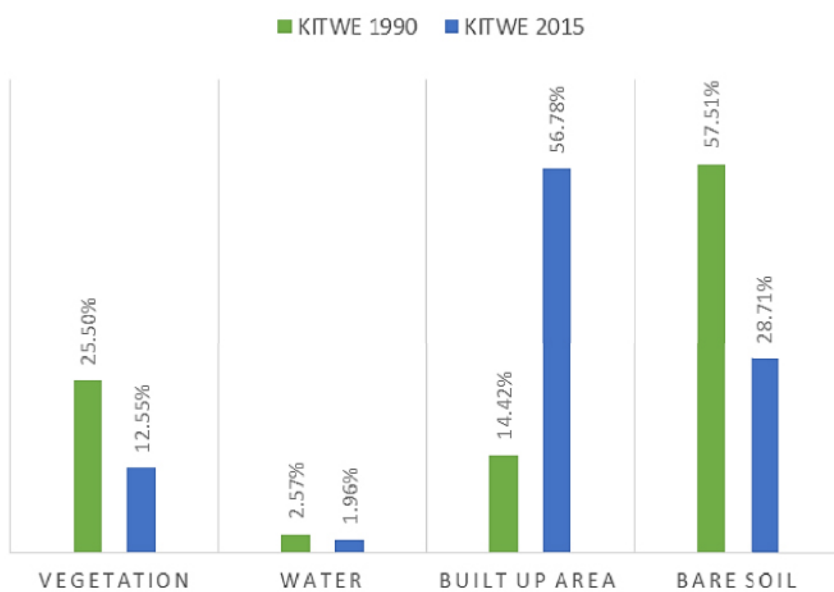

Figure 4. Land use and land cover changes in Kitwe between 1990 and 2015.

Table 1. Characteristics of Landsat TM and Landsat ETM+ sensors.

Sensor type	Thematic mapper (TM)	Enhanced thematic mapper plus (ETM+)	Pushbroom (both OLI and TIRS)
Platform	Landsat 4 (launched 16 July 1982)	Landsat 5 obtained (launched 1 March 1984) Landsat 7 (launched 15 April 1999)	Landsat 8
Orbit	16 days/705 km	16 days/705 km	16 days/705 km
Swath width	185 km	185 km	
Bands	B1 (0.45–0.52 µm) Blue B2 (0.52–0.60 µm) Green B3 (0.63–0.69 µm) Red B4 (0.76–0.90 µm) NIR B5 (1.55–1.75 µm) SWIR B6 (10.4–12.5 µm) TIR B7 (2.08–2.35 µm) SWIR-2	B1 (0.45–0.52 µm) Blue B2 (0.52–0.60 µm) Green B3 (0.63–0.69 µm) Red B4 (0.76–0.90 µm) NIR B5 (1.55–1.75 µm) SWIR B6 (10.4–12.5 µm) TIR B7 (2.08–2.35 µm) SWIR-2 B8 (0.50–0.90 µm) Panchromatic	B1 (0.435–0.451 µm) Deep blue B2 (0.452–0.512 µm) Blue B3 (0.533–0.590 µm) Green B4 (0.636–0.673 µm) Red B5 (0.851–0.879 µm) NIR B6 (1.566–1.651 µm) SWIR-1 B10 (10.60–11.19 µm) TIR-1 B11 (11.50–12.51 µm) TIR-2 B7 (2.107–2.294 µm) SWIR-2 B8 (0.503–0.676 µm) Panchromatic B9 (1.363–1.384 µm) Cirrus
Ground pixel size	30 m (bands 1–5,7) 120 m (band 6)	30 m (bands 1–5,7) 60 m (band 6) 15 m/18 m (band 8)	30 m (bands 1–7,9) 100 m (band 10–11) 15 m (band 8)

Preliminary image processing and data generation followed the building of two mosaics for the years 1990 and 2015. The spectral radiance (L_λ) was calculated using Equation (1), which converted the digital numbers (DNs) to radiance.

$$L_\lambda = L_{MIN_\lambda} + \left(\frac{L_{MAX_\lambda} - L_{MIN_\lambda}}{QCAL_{MAX} - QCAL_{MIN}}\right)(QCAL - QCAL_{MIN}) \qquad (1)$$

where:

L_λ is the spectral radiance
$QCAL$ is the calibrated and quantized scaled radiance in units of digital numbers
L_{MIN_λ} is the spectral radiance at $QCAL = 0$
L_{MAX_λ} is the spectral radiance at $QCAL = QCAL_{MAX}$

The spectral radiances were then converted to reflectivity for each band based on the metadata of the images using the following Equation (2);

$$\rho_\lambda = \left(\frac{\pi * L_\lambda * \partial^2}{ESUN_\lambda - \text{COS}\theta}\right) \quad (2)$$

where:

L_λ	is the spectral radiance
∂^2	is the inverse square relative Earth-Sun distance
ρ_λ	is the reflectance for each band
θ	is the solar Zenith angle in degrees
$ESUN_\lambda$	is the mean exoatmospheric solar irradiance

2.2.1.2. Develop indicators of vegetation and soil effects The study used NDVI as a simple graphical and numerical indicator that can be used to analyse remote sensing measurements and assess whether the target being observed contains live green vegetation or not. NDVI was computed using Equation (3). Satellite-derived NDVI measurements collected the measure of reflection in the infrared (0.73–1.10 μm) and red (0.58–0.68 μm) bands [16]. Any deviation from the normal NDVI may indicate land degradation.

$$NDVI = \frac{NIR - R}{NIR + R} \quad (3)$$

where

NIR	is the near-infrared wavelength
R	is the red wavelength

Using the BSI (Equation (4)), the study was able to assess bare soil and what role it played within Kitwe's urban ecosystem. The index was an indicator of urban expansion and exposed soil conditions. The index was used to differentiate between agricultural and non-agricultural land. BSI negative values or those near 0 represent zones with vegetation.

$$BSI = \frac{(SWIR + R) - (NIR + B)}{(SWIR + R) + (NIR + B)} * 100 + 100 \quad (4)$$

where

NIR	is the near-infrared wavelength
R	is the red wavelength
B	is the blue wavelength

Bare soil is soil or sand not covered by grass, sod, other live ground covers, wood chips, gravel, artificial turf, or similar coverings.

2.2.1.3. Land cover changes To detect land cover changes between 1990 and 2015, the change detection method was used. CVA was applied using the NDVI and BSI indices for two time points (T_1 and T_2). Therefore, given multi-date pairs of spectral measurements, the study computes spectral change vectors and compares their magnitudes to a specified threshold criterion. The decision that a change had occurred was made whenever that threshold was exceeded [27, 40]. CVA uses two spectral channels to map both the magnitude of change and the direction of change between the two (spectral) input images for each date, as shown in Figures 8 and 9.

2.2.1.4. Change magnitude To develop change magnitude (i.e., to indicate the intensity of change as derived based on the Euclidian distance), Equation (5) was used, and it gave map outputs shown in Figure 9. The developed output image was classified into four categories: low (0–15), medium (15–30), high (30–45), and very high (45–60), which represent the sum of changes occurring between the dates. The study tracked changes using equation (5).

$$M_v = \sqrt{(NDVI_{11} - NDVI_{21})^2 + (BSI_{12} - BSI_{22})^2}. \quad (5)$$

2.2.1.5. Direction of change In order to determine the direction of the change between 1990 and 2015, Equation (6) was used, which detects a pixel that corresponds with a pixel corresponding to T_1 and T_2; that is, each vector is a function of positive and negative changes occurring in the spectral bands following the equation.

$$\tan\theta = (BSI_{11} - BSI_{21})/(NDVI_{11} - NDVI_{21}). \quad (6)$$

The values between 90° and 180° represent increased vegetation cover and those between 270° and 360° represent bare soil (degradation).

2.2.1.6. Analysis of processed images To quantify the change, the study used an unsupervised classification approach using the Spatial Analyst tool in ArcGIS 10.4 after having calculated the NDVI and BSI indices. The indices were classified by a threshold value of 0.25 and then divided into four classes. Then the study calculated the percentages of each class individually to get the number of pixels per class and converted it to area.

2.2.2. Urban tree species assessment

Once the magnitude and direction of the land cover changes in the district were determined, the study focused on determining which vegetation tree species were commonly found within the town. This was done by determining the number of tree species present within the urban part of Kitwe. The initial community analysis was carried out during the rainy season to capture the peak growth of trees. This was carried out between October 2017 and December 2018.

2.2.2.1. Tree species sampling From the total urban tree population, stratified sampling was employed to develop a species list showing the top 24 common species (Figure 10) using the relative abundance method [41]. This list classified the urban trees into tree species groups (strata) to understand their distribution and dominance around the urban centre of Kitwe. Classification of over 1,758 trees located within the built-up areas and within a 15 m road radius. Further classification of the trees was made as commercial, ornamental, fruit trees, and non-ornamental (indigenous) from the ten roads that connect the 42 settlements. From the top 24 species identified, the study was confined to only evaluating the top 9 tree species usable for streets and avenues, with an additional 2 commercial species commonly grown in the plantations on the Copperbelt Province.

2.2.2.2. Sample frame Fresh leaf samples were collected from 4 mature individual urban trees identified in Table 2 in accordance with procedures by Sahu & Kumar Sahu [34]. A tree was selected randomly in a cluster to ensure geophysical uniformity between samples. These clusters were demarcated into three urban areas (Nkana East, Parklands, and Riverside) with the highest availability of all target species. This made it easier to have trees within the same age group and with similar background environments.

To determine wood-specific density for carbon sequestration, wood samples were collected following the procedures described by Chave [42]. At least two core samples per sample tree were collected. From the two common methods for determining wood density, the study used the water displacement method, considering available resources.

2.2.2.3. Collection of leaves for biochemical characterisation The study used indicative biochemical data to evaluate tree tolerance as well as show urban tree species' ability to adapt to varying environments. Biochemical data were collected from each fresh leaf sample from the forty-four sample trees. Sampling was observed over three sampling periods, accounting for 132 leaf samples obtained in total. Fresh leaf samples collected were taken to the Copperbelt University School of Natural Resources (SNR) laboratory for analysis. Biochemical data consisted of four parameters: ascorbic acid, relative water content, chlorophyll, and pH. Various laboratory apparatuses used included beakers, test tubes, clippers, and graduated cylinders, among others.

2.2.2.4. Urban tree performance data The study adopted a checklist by Kashyap *et al.* [43], Ogunkunle *et al.* [44] and Pandey and Tripathi [10] to collect qualitative data for each tree species' performance. Each species was evaluated by ticking the appropriate response relating to three main factors; laminar structure, biological and socioeconomic factors, and incorporating the tolerance of trees (see Table 3). Each factor influenced the performance of each particular species within a given

Table 2. Characteristics and binomial nomenclature of the 11 most common urban trees in Kitwe.

SN	Species name	Scientific species names	Common name/ English name	Tree type	No of trees sampled (n)	DBH (cm)
1	*D. regia*	*Delonix regia (Hook.)*	Flamboyant, Flame Tree, gold mohar	Evergreen	4	47.20 ± 13.40
2	*T. ciliata*	*Toona ciliata M.Roem*	*Toona ciliate,* Red cedar	Deciduous	12	43.64 ± 22.32
3	*J. mimosifolia*	*Jacaranda mimosifolia D. Don*	*Jacaranda,* Brazilian rose wood	Deciduous	12	29.18 ± 3.47
4	*B. variegata*	*Bauhinia variegata (L.) Benth.*	Orchid tree, camel's foot, mountain ebony	Deciduous	12	22.09 ± 5.11
5	*S. siamea*	*Senna siamea (Lam.) H.S. Irwin & Barneby*	Yellow cassia, Bombay blackwood, cassod tree, ironwood	Evergreen	9	31.18 ± 18.06
6	*S. campanulata*	*Spathodea campanulata P. Beauv.*	African tulip tree, fireball, flame of the forest, Flame tree	Evergreen	11	47.72 ± 18.16
7	*P. rubra*	*Plumeria rubra L.*	Red frangipani, pagoda tree, red-jasmine	Evergreen	10	17.91 ± 8.07
8	*G. arborea*	*Gmelina arborea Roxb.*	Candahar, melina, goomar teak, white teak,	Evergreen	12	43.27 ± 8.06
9	*S. actinophylla*	*Schefflera actinophylla (Endl.) Harms*	Umbrella tree, Australian umbrella tree, ivy tree, octopus tree	Evergreen	4	15.53 ± 13.00
10	*E. grandis*	*Eucalyptus grandis Hill ex Maiden*	Flooded gum or rose gum	Evergreen	4	10.09 ± 1.01
11	*P. oocarpa*	*Pinus oocarpa Schiede ex Schltdl*	Ocote pine, Nicaraguan pitch pine, oocarpa pine	Evergreen	4	20.78 ± 1.56

Table 3. Gradation checklist for urban tree species for API.

Grading character	Pattern of assessment	Grade allotment	Grading character
Tolerance	APTI	2.0–6.0	+
		6.1–10.0	+ +
		10.1–14.0	+ ++
		14.1–18.0	+ + + +
		18.1–22.0	+ + + ++
Biological and Socio-economic	Plant habit	Small	−
		Medium	+
		Large	+ +
	Canopy structure	Sparse/irregular/globular	−
		Spreading crown/open/semi-dense	+
		Spreading dense	+ +
	Type of plant	Deciduous	−
		Evergreen	+
Laminar structure	Size	Small	−
		Medium	+
		Large	+ +
	Texture	Smooth	−
		Coriaceous	+
	Hardiness	Delineate	−
		Hardy	+
	Economic value	Less than 3	−
		3 or 4 uses	+
		Five or more uses	+ +

Note: A maximum grade for any tree species is 16. Gradation characteristics and grades allotted were adopted from [10, 43].

environment, and each response corresponded to a given grading character (+ or −) for each parameter. The grading characters' scores are then added together to get the total, which uses Equation (7) to get the final API rating.

2.2.3. Data analysis

The information collected was analysed through the identification of common patterns, equations, comparisons of primary findings, and the statistical package SPSS. Interpretation of results and attempts to rationalise or understand the meaning of these figures and/or numbers were also considered as follows:

2.2.3.1. Remote sensing and GIS analysis ERDAS Imagine 2014 was utilised for satellite image preparation, alteration, and treatment. All image processing and adjustments were completed here. For all mapping and visualisation software for index calculation, categorization, and visualisation, ArcGIS 10.4 was utilised. Excel was also used for data analysis and calculations.

2.2.3.2. Relative abundance Classification of the introduced and most common tree species was implemented using relative abundance (RA) [41], which ranked the most commonly found urban trees around Kitwe's urban built area. RA is the number of individuals of each tree species and was summed up for all the species counted, divided by the total number of individuals in which the species occurred (see Equation (7)).

$$RA = ((TNs)/(TP)) \times 100 \tag{7}$$

where

RA	is the Relative Abundance
TNs	is the total number of individual trees per species
TPs	is the total tree population

2.2.3.3. Air pollution tolerance index (APTI) To determine the tree's tolerance and infer the tree's adaptive capacity, biochemical data were collected from the laboratory using a laboratory protocol developed and recorded in the lab book. A summary of the data analysis techniques below.

2.2.3.4. Ascorbic acid content of the leaf Ascorbic acid content (mg/g) was measured according to the methods described by Pandey & Tripathi [10]. In brief, for each 1 g sample prepared into a test tube, 4 ml of oxalic acid-EDTA extracting solution, 1 ml of orthophosphoric acid, and 1 ml of 5% tetraoxosulphate (vi) acid were added to the mixture. The mixture was stirred for a minute, after which 2 ml of ammonium molybdate and then 3 ml of water were added. The solution was then allowed to stand for 15 min, after which the spectrophotometric method as described by Bajaj and Kaur [45] was done using the absorbance at 760 nm. The concentration of ascorbic acid in the samples was then extrapolated from a standard ascorbic acid curve and recorded in the laboratory book.

2.2.3.5. Relative water content (RWC) According to the method prescribed by Liu and Ding [46], RWC was collected using the drying method. Each fresh leaf sample was weighed using an analytic scale, with the result recorded in the laboratory logbook to get the fresh weight (FW), after which the sample was placed in an airtight vial. The vial was then fully hydrated by filling it with water to full turgidity for 2–3 h at room temperature. The sample was then removed, allowed to dry off moisture using tissue paper, and immediately weighed to get the turgid weight

(TW) result. After this, the sample was placed in a drying oven to dry leaf samples at 70 °C for 24 h and weighed again to get the dry weight (DW). To calculate RWC, we used Equation (8) below.

$$RWC = ((FW - DW))/((TW - DW)) \times 10 \tag{8}$$

where:

FW	Fresh weight
DW	Dry weight
TW	Turgid weight.

2.2.3.6. Total chlorophyll The U.S. EPA and Liang *et al.* [47] described the methods used to measure total chlorophyll as follows: each fresh leaf sample was cut into smaller pieces and crushed into a homogenised sample. 0.5 g of the sample was placed into a motor and further crushed and washed with an extraction solution of 80% acetone and ammonium hydroxide (9:1, respectively) into a test tube. The leaf sample was then incubated at room temperature in a 1.5-mL tube with 1 mL of an 80% acetone solution for at least 24 h, then clarified by centrifugation for 5 min at 15,000 g. A spectrometer was used to measure the samples at distinct wavelengths for the chlorophyll methods described in the article. After extraction, a spectrophotometer measured the total chlorophyll content. In this study, the absorbance of the supernatant was measured at wavelengths 645 and 663 nm (A645 and A663). Samples having absorbance results greater than 1 were diluted by half with 80% acetone and re-evaluated. The chlorophyll concentration was estimated following Arnon's equations [48] (Equations (9)–(11)) as follows:

$$\text{Chlorophyll a } (\mu g/mL) = 12.7\ (A663) - 2.69\ (A645) \tag{9}$$

$$\text{Chlorophyll b } (\mu g/mL) = 22.9\ (A645) - 4.68\ (A663) \tag{10}$$

$$\text{Total chlorophyll } (\mu g/mL) = 20.2\ (A645) + 8.02\ (A663). \tag{11}$$

2.2.3.7. pH To calculate the leaf extract pH value, a digital pH metre was used for each leaf sample. This was done by placing about 0.5 g of leaf sample, which was crushed and homogenised in 50 ml of de-ionised water, then centrifuged, and the supernatant was collected for pH measurement.

2.2.3.8. Determination of air pollution tolerance index (APTI) From the results collected from the ascorbic acid (A), RWC (R), total chlorophyll (T), and pH (P) analyses, Equation (12) was used to assess the APTI. The mathematical expression combines the four biochemical parameters into a single rate and is based on studies by Singh and Rao [49] and Pandey and Tripathi [10].

$$APTI = [A(T + P) + R]/10, \tag{12}$$

where

APTI	is the Air Pollution Tolerance Index
A	ascorbic acid content in mg g^{-1} of fresh weight.
T	total chlorophyll in mg g^{-1} of fresh weight.
P	pH of leaf extract and
R	relative content of water in percentage.

To interpret APTI, Table 4 was used to provide categorization [2] of the index values between sensitive and highly tolerant.

Table 4. Categorization of urban trees according to air pollutant toleration index values (APTI).

APTI value	Category
4.0–5.0	Sensitive
5.0–6.0	Intermediate
6.0–7.0	Tolerant
>7.0	Highly tolerant

Sources: Okunlola *et al.* [2].

2.2.3.9. Determination of anticipated performance index (API) Based on the results from the API checklist (Table 3), each response corresponded to a given grading character (+ or −) for each parameter. Then, using the total score per species, a percentage score was evaluated using Equation (13).

$$\text{Percentage score} = (Gr)/(Gr_{\max}) \times 100, \tag{13}$$

where

Gr	is grades obtained by tree species
$Gr_{\max}$	is the maximum possible grade for any tree species

Each species' percentage score was then used to interpret the results using the classification criteria in Table 5 below, which factors in the percentage score to assign the tree category.

Table 5. Assessment criteria for grading anticipated performance index (API).

Grade	Score (%)	Assessment category
0	Up to 30	Not recommended
1	31–40	Extremely poor
2	41–50	Poor
3	51–60	Moderate
4	61–70	Good
5	71–80	Exceptionally good
6	81–90	Excellent
7	91–100	Best

2.2.4. Determining above-ground biomass (AGB)

2.2.4.1. Wood density (WD) The water displacement method was used to calculate WD. The method made volume measurement easy and reliable, even for irregularly shaped samples. Combining species-specific literature estimations and field measurements using the water displacement approach yielded the average WD. Immersing the 4.9-mm-diameter wood core samples from the sample trees in water and computing the ratio of the increase in water volume to the dry wood weight calculates water displacement.

Kettering *et al.* [50] define biomass as volume × density. Estimating the total carbon sequestered for each of the eleven tree species in urban Kitwe required WD estimates [51]. Location, temperature, and management affect urban WD. Thus, site-specific WD values are needed before using allometric equations.

2.2.4.2. Allometric equations Because the species list developed identified species with no defined local allometric equations to develop estimates, published generalised equations were used instead. The species-specific growth data gathered was then plugged into the biomass estimation allometric equation developed by Chave *et al.* [52] for tropical trees as follows:

$$AGB_{est} = 0.0673 \times (\rho D^2 H)^{0.976}, \tag{14}$$

where:

AGB	Tree biomass (estimated in kg matter per tree)
H	Height of the tree
D	Diameter at breast height
ρ	Wood density(g/cm^3)

To calculate the CO_2 according to the method described by Aguaron and McPherson [53], a multiplication factor of 0.50 was applied to the estimated AGB in kg matter per tree, and the result was further multiplied by 3.67 as shown below (Equations (15) and (16)).

$$\text{Carbon} = 50\% \text{ of Biomass} \tag{15}$$

$$\text{Carbon Dioxide} = \text{Carbon} \times 3.67. \tag{16}$$

The above equations measure AGB per tree up to the time of the study. Therefore, measurement of tree uptake of CO_2 combined with core samples was done by using incremental borers taken at dendrometer measurement positions [54] to get accurate carbon sequestration of the trees through the years of the urban tree as well as WD.

2.2.5. *Statistical assessment*

The study used biochemical data to measure urban tree species' adaptability and test the hypothesis (H_0).

2.2.5.1. Statistical software All analyses employed SPSS 20.0 (SPSS Inc., Chicago, IL, USA) with a significance threshold of P 0.05. Data was cleaned to remove significant outliers and inconsistencies. Basic descriptive tables and graphs were checked for normality before undertaking an analysis of variance (ANOVA), which is "robust" against normality breaches. The ANOVA examined sample differences. It tested the hypothesis (Ho) that all urban trees are air pollution-resistant, adaptable, and provide enough biomass for urban greening.

2.2.5.2. Rankings and comparisons After merging all three assessment tools, comparison conversations and rank analyses were conducted to select the best species for the greening programme's objectives. The study analysed species feature-by-feature to determine their similarity. Scatter plots showed how best to blend these species.

A two-tiered rating scale determines the best species for each yardstick and for all three yards. The 11 species were rated from best (1) to worst (10).

3. Results and discussion

3.1. Land cover changes between 1990 and 2015

The results of the CVA technique demonstrate several types of changes in terms of biomass growth and loss and LC changes over time. Kitwe is characterised by complex landscape changes induced by several causes, and Phiri *et al.* [55] discovered that the sources of these changes on the Copperbelt have been attributable to either natural or anthropogenic interactions with each other.

3.1.1. Land cover classification

According to the study findings, the area is primarily defined by four major classifications (see Figures 4 and 5). Between 1990 and 2015, the built-up area's LC rose dramatically while bare soil and vegetation decreased. The change vector images (Figure 5) produced from the two study periods permitted verification that the deforested area in Kitwe was 28,140 ha between 1990 and 2015. The NDVI index (see Figure 6) for this impacted area revealed a 3.45% rise in low vegetation for grasslands and agricultural fields, from 22,918 ha (1990) to 23,709.87 ha (2015). While the indigenous forest cover decreased by 24.93%, from 14,458.8 ha in 1990 to 10,853.01 ha in 2015, the NDVI index also decreased. This coincided closely with the Copperbelt Province's annual average deforestation rate of 0.84%, according to the Forestry Department (2016).

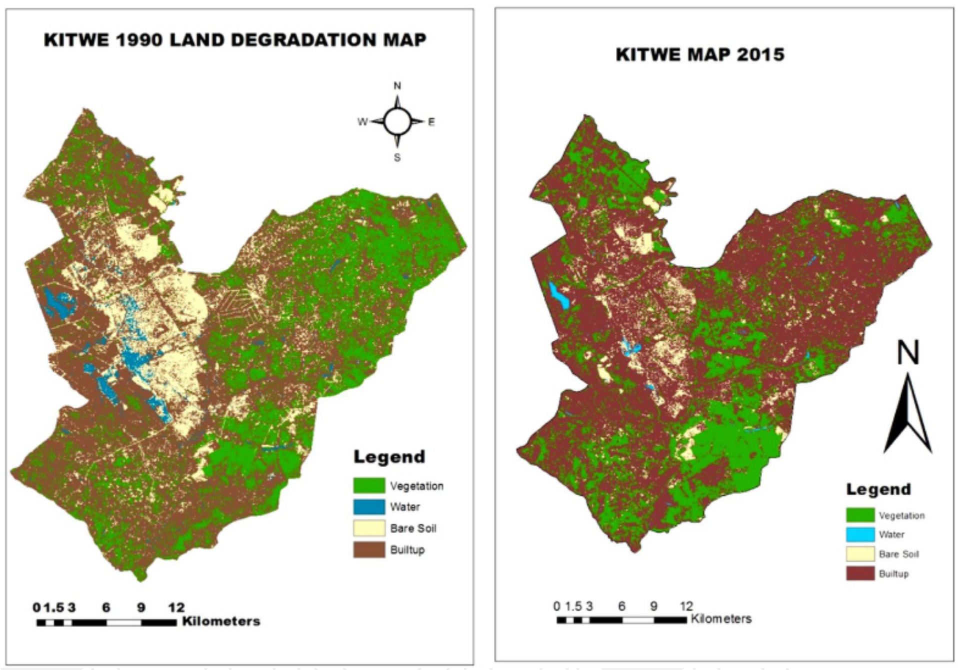

Figure 5. Land cover change classification between 1990 and 2015.

Water resources decreased by 31%, from 13,619.53 ha in 1990 to 9,393 ha in 2015, which could be linked to changes in rainfall patterns and increased water abstraction [56]. This loss could also be a direct result of expanded, developed areas and the destruction of crucial recharge sites in this district as a result of mining and agriculture [57]. Figure 4 shows a decrease in bare soil, which could be a signal to increase concrete, or Figure 7 shows a continuum ranging from high vegetation conditions to exposed soil conditions in 1990 and 2015.

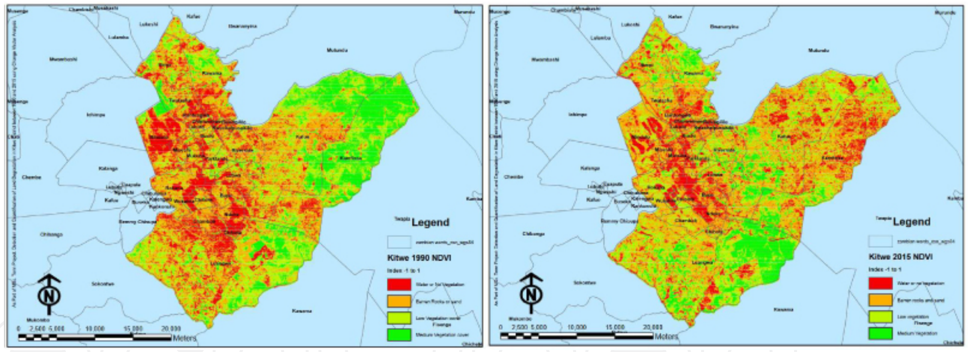

Figure 6. Map of Kitwe showing the NDVI for 1990 and 2015.

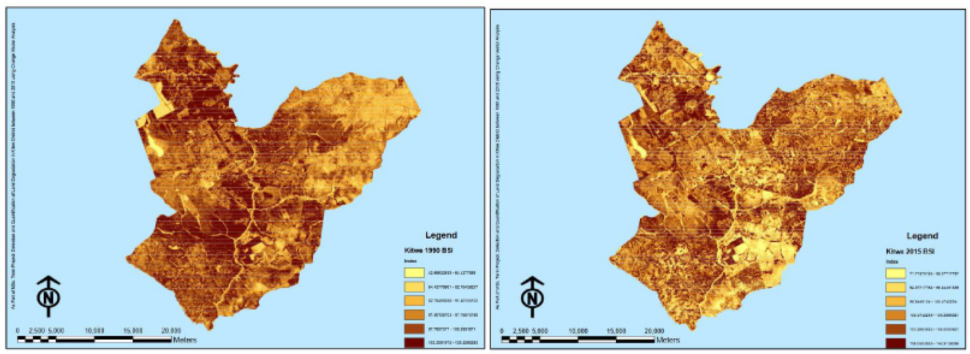

Figure 7. Map of Kitwe showing the BSI for 1990 and 2015.

3.1.2. Direction and magnitude of change in Kitwe

Figure 8 depicts the magnitude of the changes, which were relatively low within 92.94% of the district (see Table 6), demonstrating that while changes were occurring, the majority of them occurred within existing and much older communities rather than in new ones. According to the study, 6.36% of the district underwent medium-level alterations, particularly in the Northeast in regions such as Kafue and Kamfinsa, as well as parts of the CBD. The growth in built-up area is primarily owing to the city's expansion, and it is likely to continue towards the northeast as more land parcels are approved for construction.

The results suggest that 60% of Kitwe's LC is degraded (see Table 7), with the remaining 40% showing no change (see Figure 9) and covering the main CBD of Kitwe as well as mine regions. Persistence may be a trend related to the lengthy existence of urban areas and the urban activities that take place in these regions.

Other than normal urban activities, most mining-related land use increased significantly in the 1970s and early 1980s during the copper industry's boom years [58] and continue to influence land use in Kitwe. High alterations have been

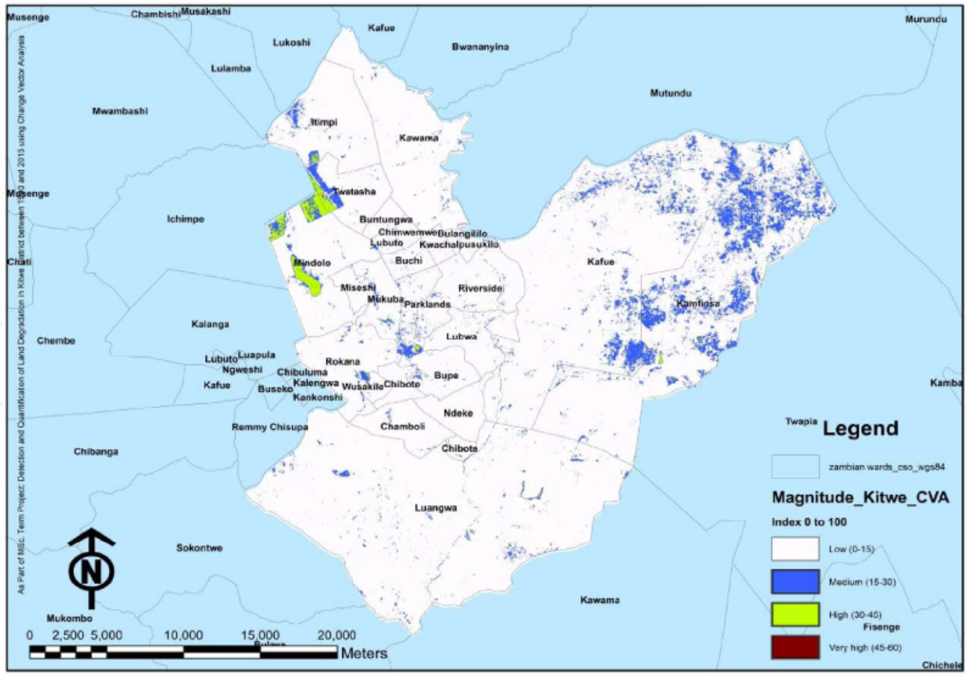

Figure 8. Map showing the change in magnitude in Kitwe district.

Table 6. Land cover magnitude area.

Kitwe magnitude (1990–2015)		
Classification	**Area (m²)**	**Percentage (%)**
Low (0–15)	741,913,200	92.94
Medium (15–30)	50,796,900	6.36
High (30–45)	5,543,100	0.69
Very high (45–60)	44,100	0.01
	798,297,300	**100.00**

Table 7. Land degradation percentage cover.

Kitwe land degradation (1990–2015)		
Classification	**Area (m²)**	**Percentage cover (%)**
Degradation	478,926,000	59.99
Persistence	319,371,300	40.01
	798,297,300	**100.00**

observed (Figure 9) in the Mindolo and Twatasha areas as a result of heavy mining activities, with much of the region being used as garbage disposal sites or tailings dams. When compared to the opportunity cost of using the land for other purposes such as agriculture and recreation, this is a loss of productive land. With the majority of the land transformed into a waste storage area, dangers from the loss of

Figure 9. Map showing Kitwe's district change direction.

isolated, unique microhabitats within an otherwise undisturbed habitat have been discovered [59] to cause the local extinction of certain plant and animal species.

3.1.3. Relative abundance of urban trees in Kitwe

As expected, the majority of Kitwe's built-up regions are composed of evergreen species rather than deciduous plants, and their continuous presence in the town is extremely likely to be the result of intentional introduction. Both introduced and indigenous species predominate. A post-hoc analysis using the Bonferroni correction found that there were no significant differences between the species groups in any of the urban tree species categories. This supports the theory that, because this is part of Kitwe's urban tree inventory, it could have come from secondary urban forest programmes that happened at varied times following the city's expansion. The top-ranking species identified (see Figure 10) as the most abundant species within the urban built-up region were *Delonix regia* (15.9%) and *Mangifera indica* (12.3%). More intriguingly, despite the fact that it was assumed that largely built-up areas would have introduced species rather than indigenous species, this was not the case. The more indigenous trees were less numerous within the built-up natural environment due to extensive forest loss caused by clearance during urbanisation.

Despite the city having lost most of its indigenous green spaces, which have been converted into residential or commercial sectors over time, more indigenous species

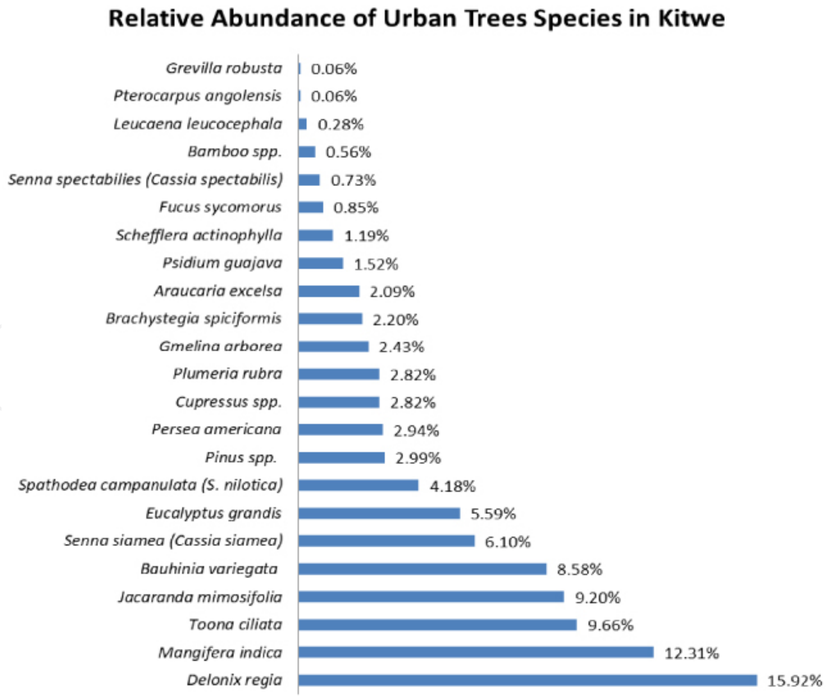

Figure 10. Relative abundance of urban trees species in Kitwe.

are regularly scattered about the city in small spaces. *Albizia antunesiana*, *Albizia versicolor*, *Baphia bequaertti*, *Branchiostegal boehmii*, *Brachystegia utilis*, *Isoberlinia angolensis*, *Julbernardia paniculata*, *Pericopsis angolensis*, *Uapaca kirkiana*, and *Uapaca nitida* are among the indigenous species identified in Kitwe City. These findings are consistent with local authority reports [38], which reveal that many of the current green spaces still support the identified species as well as many additional indigenous species.

In comparison to other towns like Mufulira, Kalulushi, Ndola, and Lusaka, these species are located along comparable sidewalks, roads, and avenues surrounding the city's main metropolitan areas, forming homogenous habitats or green spaces. This analysis indicated that the prevalent selection procedures were derived from Commonwealth town planning systems, which were modelled after British practise and legislation. The study refers to research by Home [60], who confirms that the roots of these introduced species can be traced back to pre-colonial Northern Rhodesian times (now known as Zambia), when these areas were still being planned for as townships. Home [60] goes on to explain Lusaka's reputation as a garden city, referring to "Dutton's initiative" that constructed a chain of nurseries and planted various trees in Lusaka and sections of the Copperbelt, including the ones in this article.

3.1.4. Adaptive capacity of Kitwe's urban trees

After determining the most abundant species, the study analysed the plants' ability to cope with environmental conditions by measuring plant sensitivity to their surroundings and carbon sequestration. The tree's sensitivity was characterised in connection with its exposure to its environment and air pollution, which was very likely to occur in built-up areas. The focus of adaptive capacity was the ability of species groupings to respond to specific sorts of hazards—in this example, drought, plant health, and biochemical air pollution. These responses assist the urban trees in regenerating and/or adapting in order to reduce susceptibility and increase reaction time. According to Flórez Bossio *et al.* [61], urban adaptive capacity traits can be viewed as a collection of variables that allow urban trees to adapt. After all, the resilience of urban trees and their socioeconomic value influence their abundance as well as the health of any urban forest.

The laboratory test findings revealed biochemical differences (p-value 0.05) in the means of pH, RWC, AA, and total chlorophyll content (TChl) among the three urban tree species groups (Table 8). There are significant comparison pairings in the post-hoc comparisons using the SPSS Bonferroni correction. Trees are more flexible due to their drought resilience and water efficiency. The study looked at how different tree species react to air pollution. This research is founded on three fundamental assumptions. As high pH increases stomatal sensitivity, urban trees are more resistant to air pollution. Urban tree species with high RWC maintain physiological balance and improve drought resilience. Ascorbic acid is required for cell wall growth, defence, and cell division in trees, in addition to photosynthesis for carbon dioxide fixation and antioxidant defence in urban plants. As TChl decreases with pollutant levels, urban trees with high TChl can survive air pollution and are healthier.

The overall pH ranged between 4.67 and 6.80, with *Bauhinia variegate* and *Toona ciliate* having the highest pH. As a result, urban trees in Kitwe's built-up area have better tree health and are more resistant to diseases caused by stomatal sensitivity as a result of air pollution. Compared to *Pinus oocarpa*, *Jacaranda mimosifolia*, and *Eucalyptus grandis*, which had the lowest pH and were below the supposed ideal pH (between 6.0 and 7.0), at pH levels above 6.4, urban trees are vulnerable to insect attacks, while at pH levels below 6.4, trees are vulnerable to specific diseases.

Table 8 shows that the RWC was regularly distributed, with a mean of 65.39% (SD = 1.17). RWC values for urban tree species in Kitwe were in the higher range, i.e., between 50% and 90%. This was greatest in *Schefflera actinophylla* and *Bauhinia variegate* and lowest in *Jacaranda mimosifolia*. Since urban trees can improve water resilience in cities, the majority of Kitwe urban tree species identified have sufficient RWC to maintain tree physiological balance and improve other key sensitivity

Table 8. APTI value for common urban trees in Kitwe.

SN	Species name	DBH (cm)	Height (m)	No of trees (N)	No of leaf samples (n)	pH	Ascorbic acid	RWC (%)	TChl	APTI	Categorization
1	*Delonix regia*	47.20 ± 13.4	10.99 ± 2.95	4	12	5.821 ± 0.281	0.0928 ± 0.085	59.368 ± 18.068	0.692 ± 0.704	5.99 ± 1.76	Intermediate
2	*Toona ciliata*	43.64 ± 22.32	17.29 ± 2.39	12	12	6.415 ± 0.263	0.0801 ± 0.027	70.459 ± 25.693	1.225 ± 0.419	7.11 ± 2.58	Highly tolerant
3	*Jacaranda mimosifolia*	29.18 ± 3.47	12.33 ± 0.96	12	12	4.997 ± 0.413	0.0327 ± 0.017	56.025 ± 7.924	1.132 ± 0.691	5.62 ± 0.79	Intermediate
4	*Bauhinia variegata*	22.09 ± 5.11	10.55 ± 2.07	12	12	6.815 ± 0.577	0.0537 ± 0.034	78.800 ± 5.800	2.387 ± 4.334	7.93 ± 0.60	Highly tolerant
5	*Senna siamea* (*Cassia siamea*)	31.18 ± 18.06	10.56 ± 1.71	9	12	6.148 ± 0.456	0.1131 ± 0.095	50.734 ± 23.044	1.763 ± 3.257	5.16 ± 2.27	Intermediate
6	*Spathodea campanulata* (*S. nilotica*)	47.72 ± 18.16	10.31 ± 5.23	11	12	5.955 ± 0.209	5.9553 ± 0.209	56.432 ± 24.608	0.586 ± 0.618	5.68 ± 2.45	Intermediate
7	*Plumeria rubra*	17.91 ± 8.07	9.18 ± 2.94	10	12	5.884 ± 0.208	0.0109 ± 0.006	74.673 ± 29.467	0.727 ± 0.598	7.47 ± 2.95	Highly tolerant
8	*Gmelina arborea*	43.27 ± 8.06	13.92 ± 1.49	12	12	6.303 ± 0.390	0.1260 ± 0.086	61.549 ± 32.19	0.242 ± 0.239	6.24 ± 3.18	Tolerant
9	*Schefflera actinophylla*	15.53 ± 13.00	8.11 ± 5.42	4	12	5.926 ± 0.499	0.0199 ± 0.016	80.996 ± 16.018	0.507 ± 0.570	8.11 ± 1.61	Highly tolerant
10	*Pinus oocarpa*	10.09 ± 1.01	6.96 ± 0.8	4	12	4.669 ± 0.179	0.1523 ± 0.090	70.633 ± 13.602	0.638 ± 0.791	7.15 ± 1.37	Highly tolerant
11	*Eucalyptus grandis*	20.78 ± 1.56	15.35 ± 2.18	4	12	5.267 ± 0.213	0.0858 ± 0.110	59.617 ± 31.006	0.826 ± 0.603	6.01 ± 3.05	Tolerant
				94	***132***	***5.84 ± 0.340***	***0.61 ± 0.07***	***65.39 ± 20.68***	***0.98 ± 1.17***	**6.59 ± 2.35**	

aspects such as drought tolerance. Drought tolerance indices [62] can be used to learn more about how environmental conditions influence this.

There was a statistically significant difference in the means of TChl between the various urban tree species groups. When compared to other species, *Toona ciliate* and *Jacaranda mimosifolia* have the highest TChl, while *Delonix regia* and *Bauhinia variegate* have the lowest. The presence of a high concentration of chlorophyll in these urban trees boosts their tolerance to air pollution and serves as an indirect indication of urban tree health. It should be emphasised, however, that the TChl declines as pollution levels rise. Significant comparison pairings were discovered using post-hoc comparisons with the SPSS Bonferroni correction.

Pinus oocarpa had the highest ascorbic acid concentration, while *Plumeria rubra* had the lowest (Table 8). These urban tree species with a high ascorbic acid content are more suitable because ascorbic acid is required for cell wall synthesis, defence, and cell division in trees, is required for photosynthesis for carbon fixation, and acts as an antioxidant, increasing urban tree resistance to their natural environment.

Vulnerability, as it relates to the socioeconomic elements of the tree species, covered numerous aspects such as the aesthetic value of trees as well as the minimal demand for care and maintenance, which is the major criterion for use, particularly in urban management [63]. Take, for example, *Delonix regia*, the most prominent species in the research area, which is known for its dense clusters of orange-red flowers that bloom in early summer and have a vibrant hue that makes it appealing. Furthermore, the species was discovered to be native to Madagascar and Zambia and has been introduced in many other countries, becoming widespread in most tropical and subtropical areas of the world [64]. Another popular species is *Jacaranda mimosifolia*, which is known for its clusters of beautiful bell-shaped, blue-violet flowers that provide both beauty and shade.

The observations in Kitwe reveal that natural indigenous plants are subject to challenges from invasive species that are known to enter forest gaps, plantations, roadsides, and riparian zones (banks of watercourses) (ibid.). These have a large impact on Kitwe's urban forest inventory because they are abundant in the built-up areas. CAB International classifies *Jacaranda mimosifolia* as an invasive species because this urban tree, which is native to South America, is highly competitive and does not allow other urban trees to grow beneath it [63]. T. ciliate and S. campanulate are two other instances. While both are invasive species, it was discovered that T. ciliate is a more aggressive invasive species than S. campanulate. Furthermore, S. campanulate is a more popular ornamental tree than T. ciliate, which has no attractive flowery attributes but is widespread due to its indigenous status [63, 65]. Other species, such as *Mangifera indica*, are abundant because of their fruit-bearing ability and ability to provide shade for residents [66]. As a result, these evergreen trees are more sheltered and grow well in locations with a short dry season.

Kitwe city land use dynamics posed an additional threat to the city's urban forest's ability to survive change. According to Phiri *et al.* [55], while examining trends in spatial distribution of such urban green areas improves understanding of forest management, this is not always the case. Kitwe is distinguished by complex terrain changes induced by natural and man-made forces interacting with one another. Threats such as a lack of soil naturing programmes to enhance soil quality, on the other hand, continue to shorten the life span of trees in what were formerly green regions with degraded soils [67]. This became an opportunity and the primary focus of urban forest management.

3.1.4.1. APTI of urban trees Following the biochemical analysis, the APTI was used to determine which trees are appropriate species for urban greening programmes focused on mitigating or adapting to air pollution. According to the APTI data (Table 8), *Schefflera actinophylla* is the most tolerant, followed by *Plumeria rubra*. *Senna siamea (Cassia siamea)* was the least tolerant of the eleven species tested. Furthermore, the analysis revealed that the APTI results differed significantly between species types (F (10,121) = 2.453, p = 0.0105). The tree species least vulnerable to air pollution is also the most tolerant. As a result, such plant species can be prioritised for planting programmes in urban built-up areas and industrial areas, reducing the effects of air pollution and making the ambient atmosphere clean and healthy. Popular species such as *Cassia siamea* and *Jacaranda mimosifolia* were discovered to be the least tolerant and thus the most vulnerable to air pollution.

According to the box plots for comparative species groups (see Figure 11), only four species groups (JM, BV, SA, and PO) have a high level of agreement with each other, while the rest of the data are dispersed across groups. These could be the result of various environmental factors, some of which could only be revealed by gaining access to the biological parameters. The results of the biochemical analysis (Table 8) of plants revealed species variation, which may be attributed to environmental variables such as shifting soil profiles throughout the city, which results in varying soil quality [67], and the age of the tree [68]. Such factors have been shown to have a direct effect on the two key parameters, ascorbic acid and TChl [69], and have been identified as the most significant contributors to species differences when compared to pH and RWC. This means that all common plants in a specific metropolitan location can be classified according to their sensitivity or tolerance to air pollution.

3.1.4.2. API of urban trees When the results are compared to the plants' socioeconomic characteristics (Table 9), the highest API is found in *Eucalyptus grandis*, *Bauhinia variegate*, and *Gmelina arborea*, while *Schefflera actinophylla* and

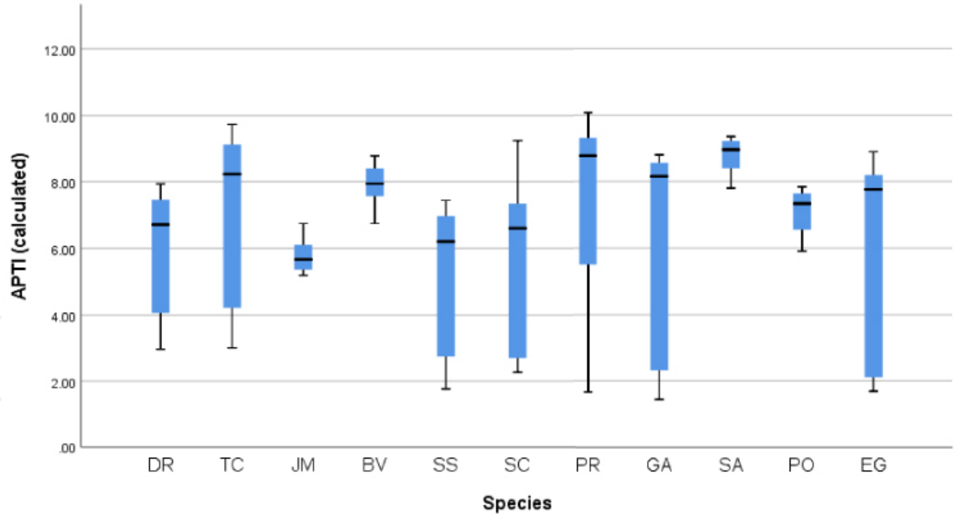

Figure 11. Boxplot of APTI by species.

Plumeria rubra are the least poor-performing tree species. Furthermore, the findings show that the best species identified, *Eucalyptus grandis*, has a dense canopy of evergreen foliage and is well known for its economic value rather than its aesthetic value [63, 64]. As API is based on various factors influencing plant performance, including socioeconomic aspects, it contributes to a better understanding of the sustainability of greening programmes. By ensuring that acceptable plant species deliver more value, green programmes should try to understand elements of tree species other than only environmental biochemical parameters. Aesthetics is typically the decisive element, but it was shown that despite the plant species lacking flowery features, some species are nonetheless prominent inside Kitwe. This is due to other characteristics, such as fruit-bearing properties, which were only found in residential neighbourhoods and not along walkways and parks.

3.1.5. AGB of urban trees

Kitwe's urban forest had the highest WD (0.662 g cm^{-3}) among *Eucalyptus grandis* species and the lowest (0.220 g cm^{-3}) among *Spathodea campanulata* species, as shown in Table 10. The variation in WD results could be best described by Deng *et al.* [70], who show that such results can be greatly influenced by site quality, relative heights, tree age, and social class of the forest inventory. These signals must be used with caution, as there may be minor differences in findings between places. The results also show that the largest contributors to carbon sequestration are *Delonix regia* and *Toona ciliate* (see Table 11), both of which are the most abundant species in town when compared to the other nine species. *Senna siamea (Cassia siamea)* came in third, and *Jacaranda mimosifolia* came in fourth, respectively. The majority of the urban trees discovered contribute to CO_2 absorption at the city level.

Table 9. Anticipated performance index (API) of different tree species in Kitwe city.

SN	Species name	APTI	Plant habit	Canopy structure	Type of plant	Size	Texture	Hardness	Economic value	Total plus (+)	API grade	% Scoring	Assessment category
1	*Delonix regia*	+	+	+ +	+	+	–	+	+	8	3	52.94	Moderate
2	*Toona ciliata*	+ +	+ +	+ ++	+	+ +	–	+	–	11	3	58.82	Moderate
3	*Jacaranda mimosifolia*	+	+	–	–	+	–	+	+ +	6	1	35.29	Extremely poor
4	*Bauhinia variegata*	+ +	+ +	+ ++	–	+	+	+	+ +	12	4	64.71	Good
5	*Senna siamea (Cassia siamea)*	+ +	+ +	+ +	+	+	–	+	+ +	11	3	58.82	Moderate
6	*Spathodea campanulata*	+	+	+ +	+	+ +	–	+	+	9	3	52.94	Moderate
7	*Plumeria rubra*	+	+	+	+	–	–	+	+ +	7	2	41.17	Poor
8	*Gmelina arborea*	+ +	+ ++	+ +	–	+ +	–	+	+ +	12	4	64.71	Good
9	*Schefflera actinophylla*	+	–	–	+	–	+	+	+	5	0	29.41	Not recommended
10	*Pinus oocarpa*	+	+ ++	+	+	+ +	–	+	+ +	11	4	64.71	Good
11	*Eucalyptus grandis*	+ +	+ ++	+	+	+ +	+	+	+ +	13	5	70.59	Exceptionally good

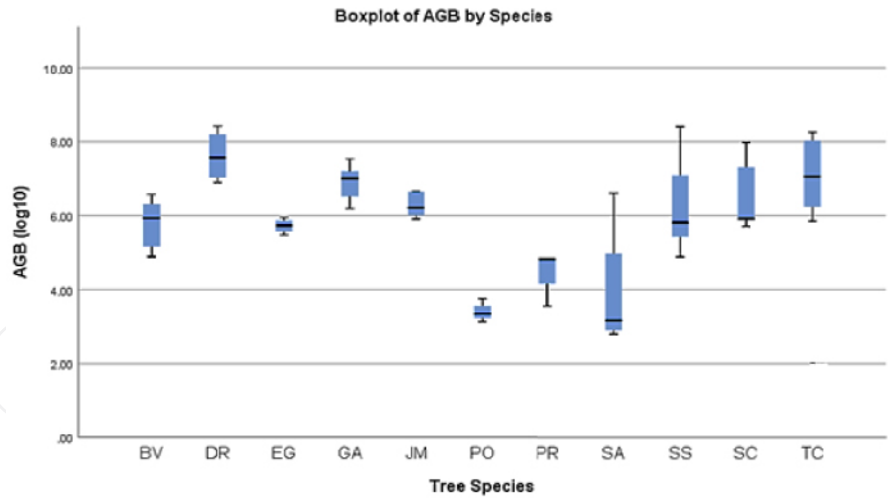

Figure 12. Above-ground biomass for the eleven urban trees in Kitwe's main roads.

However, it was discovered that species with high tolerance, such as *Schefflera actinophylla*, contribute less to carbon capture.

The fact that variance is modest (see Figure 12) may be attributed to the species' ability to sequester carbon as well as the species' abundance in urban areas. The ability of urban forests to sequester carbon is determined by various aspects, including (1) the age of the tree, (2) its size, (3) environmental considerations, and (4) policy and methods of generating deliberate enabling elements that enable such greening programmes. These considerations stem from the observation that there are considerable changes in carbon sequestration results between tree species (see Table 10) due to the difference between young and older urban trees. Anwar [68] verified this, arguing that older trees have lived longer and have had more time to store carbon than younger urban forests. According to the findings of this study, the two commercial tree species are young urban trees with extremely low biomass (Table 10). This has a substantial impact on each tree's biochemical characteristics. For example, TChl varies over the tree's life cycle. Table 8 displays how TChl changes depending on species, leaf age, pollution level, and other biotic and abiotic variables [71]. Certain pollutants increase TChl, while others decrease it [72].

3.1.6. Suitability trees for urban greening

Disaggregating all of the findings from APTI, API, and AGB reveals (see Table 11 and Figures 13–15) that there are disparities between the species groups, with the data being closely spread, showing a high level of similarity, and the rest of the results being scattered between groups. These could be the result of exposure to various environmental factors and the influence of certain functional groups.

Table 10. Carbon sequestration for the top 11 common tree species in Kitwe.

SN	Species name	Wood specific gravity (g cm^{-3})	Average AGB (kg matter per tree) *	Number of trees in Kitwe urban	Carbon uptake		
					Total AGB in Kitwe urban (kg)	Carbon uptake in Kitwe urban (kg)	CO_2 uptake in Kitwe urban (kg)
1	*Delonix regia*	0.579	867.89 ± 650.58	282	244,744.72	122,372.36	449,106.56
2	*Toona ciliate*	0.376	1,197.63 ± 1132.22	171	204,793.92	102,396.96	375,796.84
3	*Jacaranda mimosifolia*	0.490	289.69 ± 167.1	163	47,220.09	23,610.04	86,648.86
4	*Bauhinia variegata*	0.653	130.41 ± 83.45	152	19,821.98	9,910.99	36,373.34
5	*Senna siamea (Cassia siamea)*	0.650	533.35 ± 632.07	108	57,602.08	28,801.04	105,699.83
6	*Spathodea campanulata (S. nilotica)*	0.220	395.55 ± 386.92	74	29,270.45	14,635.22	53,711.27
7	*Plumeria rubra*	0.500	113.20 ± 136.76	50	5,660.02	2,830.01	10,386.14
8	*Gmelina arborea*	0.340	501.22 ± 212.62	48	24,058.79	12,029.40	44,147.88
9	*Schefflera actinophylla*	0.413	119.34 ± 216.66	21	2,506.20	1,253.10	4,598.87
10	*Pinus oocarpa*	0.662	18.52 ± 4.63	53	981.38	490.69	1,800.83
11	*Eucalyptus grandis*	0.440	240.31 ± 32.18	99	23,790.60	11,895.30	43,655.75

Note: * The average AGB is for each species.

In all comparisons, the overall associations were statistically significant (Figures 13–15). Three species, *B. variegata*, *T. ciliata*, and *P. oocarpa*, were identified as the best-performing urban trees for greening programmes that prioritise tolerance and performance (Figure 13). The overall design of such greening programmes would consider the quality and purpose of development programmes that include the vulnerability of urban forests, including climate variability and adaptive characteristics. This necessitates a shift in focus on how to design robust and improved city-focused frameworks that deal with air pollution and new emerging threats [58, 73]. This should provide guidance to urban planning experts on taking carbon stocks seriously [74, 75]. There is no doubt that the best-ranking tree species should be resistant to air pollution while also contributing to carbon capture within Kitwe.

When AGB and APTI (Figure 14) are compared, it is clear that while most species had low AGB, the species varied in terms of their tolerance to air pollution, implying a negative association. A statistically significant linear association ($r = -0.195$, $p < 0.05$) exists between an increase in AGB and a drop in APTI. DBH was found to be a somewhat better predictor of APTI than AGB. Despite its weakness, the negative relationship can be attributed to the area's environmental conditions, and it also suggests that growth parameters are reduced in highly polluted areas compared to those in low air pollution areas (see Figure 14). The findings of AGB and API (Figure 15) are comparable to the combination of APTI and AGB. The amount of biomass accumulated by high-performing urban trees is not the only factor influencing their performance.

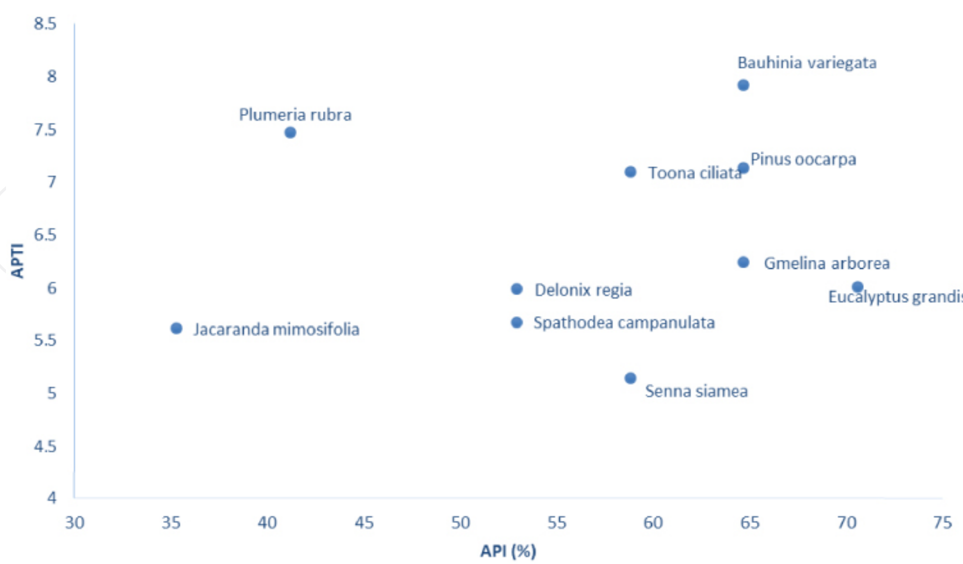

Figure 13. Comparison between urban tree tolerance (APTI) and performance (API).

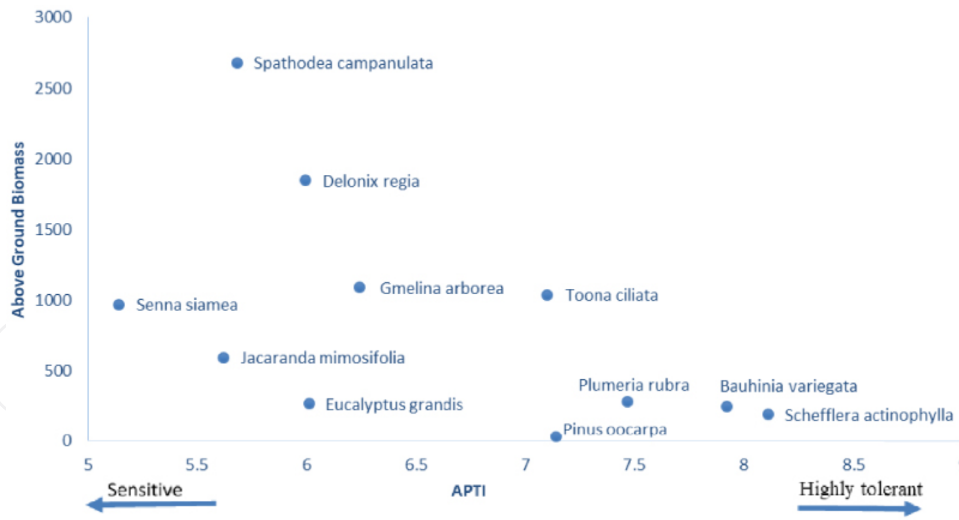

Figure 14. Comparison between species AGB and APTI.

Figure 15. Comparison between tree species AGB and API.

After integrating each assessment evaluation, each species was evaluated from best (1) to worst (10) (see Table 11). The most suited trees were *B. variegate* and *T. ciliate*, which were placed first and second, respectively. The highest-ranking tree species are resistant to air pollution while also contributing to carbon capture within Kitwe. However, it was discovered that species with high tolerance, such as *S. actinophylla*, contribute less to carbon capture.

The findings for APTI, API, and carbon sequestration are consistent with those of Jim [67] and Bowler *et al.* [76], who advocated a more empirical selection criterion for Zambian urban planners that considers factors other than aesthetics. Urban trees

Table 11. Scoring and rank of urban trees in Kitwe score.

SN	Species name	AGB rank	APTI rank	API rank	Score	Overall rank
1	*Bauhinia variegata*	8	2	2	12	1
2	*Toona ciliata*	2	5	5	12	1
3	*Gmelina arborea*	6	6	3	15	2
4	*Eucalyptus grandis*	7	7	1	15	2
5	*Delonix regia*	1	8	7	16	3
6	*Pinus oocarpa*	11	4	4	19	4
7	*Senna siamea (Cassia siamea)*	3	11	6	20	5
8	*Plumeria rubra*	9	3	9	21	6
9	*Spathodea campanulata (S. nilotica)*	5	9	8	22	7
10	*Schefflera actinophylla*	10	1	11	22	7
11	*Jacaranda mimosifolia*	4	10	10	24	8

Note: A species with the best score out of 11 for each criterion, is rated as 1, second spp as 2.

with high APTI and API ratings are proposed as species for the area's urban greening programmes. Because they are based on parameters with significant biological and socioeconomic characteristics, APTI and API can be used.

To address the vulnerability dynamics of urban forests, urban planners should establish socioeconomic scenarios and follow and trace development trends and routes while designing adaptation solutions. Understanding urban trees' sensitivity to air pollution, socioeconomic performance, and capacity for carbon sequestration will help in achieving these goals the best. Having high APTI and API values, as well as high carbon sequestration, should be promoted for new development areas employing properly developed urban greening programmes and giving specific adaptive capacity ranges [61]. These tree species could be incorporated into the design of an urban greening programme to help with long-term air pollution planning.

Kitwe's main metropolitan areas have made considerable contributions to reducing air pollution and boosting carbon absorption, thereby increasing the city's carbon stocks (see Table 10). All of the urban trees evaluated in Kitwe perform admirably in their surroundings, and there are substantial variances in tree species APTI, adaptive capacity metrics, and cumulative biomass. *Gmelina arborea*, *Toona ciliata*, and the two commercial trees are the best performing trees for high-pollution areas because they can tolerate the significant pollution from emissions. The best five species identified using rank analysis were *Bauhinia variegate*, *Toona ciliate*, *Gmelina arborea*, *Eucalyptus grandis*, and *Delonix regia*. Tables 9 and 10 indicate that each index revealed that greening programmes could combine species during the design or planning stage to achieve specific programme objectives. As a result, the decision should always be based on the purpose, location, and area development requirements.

Depending on the objective goals of the greening programme, one can compare one tree species to another to find the most effective combination that meets developmental needs that prioritise the climate variability of urban tree species as well as air pollution tolerance. The combination in Figure 15 allows urban planners and managers to assess trees suited for greening programmes aimed at improving air quality, providing shade, and improving aesthetics in low-pollution green spaces, houses, and sidewalks.

The application of APTI, API, and carbon sequestration in green infrastructure design gives planners a notion of which tree species might ameliorate air pollution and provide effective ecosystem services for urban greening programmes. The lack of air pollution data to establish a pollution gradient to compare our data between highly contaminated and less polluted areas is one of the study's limitations. Furthermore, there was insufficient data on urban tree care services near the trees sampled to provide a comprehensive methodological approach to forest management. According to Nayak *et al.* [77], growth characteristics are lowered in highly polluted areas compared to species found in low-polluted areas. This agrees with Escobedo *et al.* [78], who state that urban greening strategies suggest that planners develop networks of areas to better harness their socio-ecological components in a way that can conserve ecosystems while providing essential benefits to a given society.

4. Conclusion

The goal of this study was to assess how the land cover of the city of Kitwe had changed and to pinpoint any impacts on the urban forest that predominates there. The study's findings suggest that remote sensing can help with SDG 11 objectives 6 and 7, which are concerned with reducing the negative environmental effects of urbanisation and enhancing the layout of green places. In addition to providing visualisation in the form of maps of Kitwe, remote sensing and GIS also assist in providing a clear indicator of change and tracking and monitoring the direction and scale of city expansion. The study was successful in developing a thorough picture of how the vegetation changed between 1990 and 2015. According to the study, LC changes have occurred in Kitwe partly as a result of mining activity and urban growth. While the central business district still exhibits a persistent presence as a result of the town's age, having sprung up before the 1990s with more expansions in the newly developed areas, the areas being monitored showed low and medium change intensity, mostly in the northeast of the district. According to the data gathered, Kitwe City's built-up area is home to a variety of native and exotic tree species. Plant sensitivity to their environment and their capacity to store carbon in built-up areas were used in the study to evaluate the plants' capacity to deal with environmental conditions.

Kitwe has the top 24 common tree species, 11 of which were evaluated out of the 1758 trees found in the built-up region along the main roads and highways. The majority of the urban forests in Kitwe are made up of a variety of ornamental trees, which are frequently grown for their aesthetic value, attractiveness, and shade. According to the research, this mixture also includes opportunistic urban trees (invasive species) and fruit-bearing trees intermingled with native species. The study found the most common species and the direction of the city's land changes, and it concluded that the newer areas for land development would need greening programmes that could incorporate an efficient plan that satisfies both the city's and the plant's capacity for adaptation at the design/planning stage. Therefore, the decision should always be based on the objective, geographic location, and needs of local development in areas northeast of the district. *Schefflera actinophylla* was exceptional for urban greening because of its high tolerance and strong ability to adapt to air pollution, but it fell short in terms of being a top performer. In terms of total ranking, *Bauhinia variegata* came in second. Popular species like *Cassia siamea* and *Jacaranda mimosifolia* received low scores, indicating that they were the species least resistant to air pollution among those evaluated in Kitwe. *Delonix regia*, *Mangifera indica*, *Toona ciliate*, *Jacaranda mimosifolia*, and *Bauhinia variegate* were the top five most commonly encountered tree species.

4.1. Recommendations

Informing the public about the importance of vegetation, as some of these trees may be donated and planted in public places such as schools as part of city-wide programmes to maintain and conserve urban forests. Although all eleven species may live in low-pollution environments, it is best to keep them away from highly polluted areas such as industrial zones, roads, and highways. The study found that policy and regulation should be strengthened to be more reliable in terms of providing standard regulatory tools that impact green infrastructure (GI) expansion within cities and towns. This will aid in the development of robust, efficient, and successful urban regions.

The amount of carbon that could hypothetically be absorbed would provide annual carbon sequestration. Such data is useful for measuring urban forest production and ensuring the long-term viability of air pollution mitigation techniques, even when they are part of GI. It is also advised that local governments promote suitable species to counteract the biodiversity loss brought on by various urban development initiatives by deliberately creating an enabling environment. It is strongly advised that the API grading process include a broader range of appropriate stakeholders. Expert panels and focused interviews should be used to help understand the socioeconomic issues. It is recommended to use APTI and API together since API improves the selection criteria for acceptable plants. Furthermore, local governments should attempt to safeguard some of the endangered species by developing habitats for them and/or building neighbourhoods that not only provide food, shelter, and shade but also improve air quality, thereby avoiding species extinction.

4.2. Future research recommendations

It is recommended that the existing urban management system be replaced and that additional studies be performed to construct a selection framework. (1) The framework would expand on this study to offer a theoretical comprehension of the methods used to choose suitable plants. (2) Evaluate the regulatory structure and determine whether or not the measuring system is current. (3) Make sure the metrics align with regional and national standards. (4) Make it easy to compile a database of findings. It is recommended that future studies investigate the effects of climate change on urban tree species as well as the connections between APTI and carbon sequestration.

Conflict of interest

The authors declare no conflict of interest.

Authors' contributions

David Agamemnon Banda was responsible for the study's conception, analysis, documented sample methodology, and initial drafting. This entails overseeing both the study's analyses and the corresponding literature searches.

Acronyms and abbreviations

AGB	Above-ground biomass
ANOVA	Analysis of variance
API	Anticipated performance index
APTI	Air pollution tolerance index
BGB	Below-ground biomass
CBU	Copperbelt University
CO_2	Carbon dioxide
$[CO_2]$	Atmospheric CO_2 concentration
DBH	Diameter at breast height
DW	Dry weight
FW	Fresh weight
GPS	Global positioning system

KCC	Kitwe City Council
MRML	Most recent mature leaf
NBS	Natural-based solutions
RA	Relative abundance
RWC	Relative water content
TChl	Total chlorophyll
TW	Turgid weight

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Source data

Source data (raw scientific data accompanying the research) for this article is available on Figshare: https://doi.org/10.5772/geet.deposit.c.6830907.v1

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