Biomass supply and temperature regulation by urban forests In Puerto Carreño, Vichada-Colombia

Diana Lucia Giraldo-Charria

Universidad del Rosario
Facultad de Ciencias Naturales
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Director

PhD Benjamin Quesada

Co-director

PhD Francisco J. Escobedo

Tutor

PhD Benjamin Quesada

Facultad de Ciencias Naturales
Maestría en Ciencias Naturales
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Summary

Urban forests are considered a key element in the ecological structure of cities, contributing to the provision of ecosystem services such as carbon sequestration and climate regulation. However, few studies have investigated these regulating services in small Neotropical cities. The aim of this study was to estimate the biomass supply and carbon sequestered by urban trees, as well as to evaluate the capacity of trees in thermal regulation during the hottest season in 2021 (from December 2020 to May 2021) in Puerto Carreño - Colombia. Accordingly, we implemented random sampling through 200 circular plots to estimate the biomass and carbon storage of trees. Moreover, we used 16 digital iButton sensors located in paired sites (unshaded and tree-shaded) in eight ground covers in the city to measure hourly temperature and humidity for six months. We find that urban forests in Puerto Carreño have relatively high tree diversity and complex vertical structures, greater than that of more populated cities in the region, and high carbon storage (in a range between 37 - 51 tC/ha). Thermal regulation by urban forests increases exponentially with the ambient temperature i.e. 7,5°C at 44 °C but 2°C at 34,9°C. Specifically, during higher daily heat extremes, cooling effects are maximized by neotropical urban forests. Relative humidity is generally greater in shaded areas versus unshaded areas, which is even more pronounced during critical hot periods. Under a global context, Puerto Carreño has a high risk to develop a deadly combination of climatic conditions for temperature and humidity. Very high discomfort indexes are considerably mitigated by urban forests by a factor of 10 during the hottest hours (9 a.m. to 4:00 p.m.). On site surveys confirmed that people perceive the well-being effects of trees and their climate regulating services: tree shade and fruit provision were the key ecosystem service benefits mostly identified by residents. Our study shows that tropical urban forests are key local and global mitigation (carbon stocks) and adaptation (extreme heat reduction) measures to fight climate change.

Resumen

Los bosques urbanos se consideran un elemento clave en la estructura ecológica de las ciudades, contribuyendo a la provisión de servicios ecosistémicos como el secuestro de carbono y la regulación climática. Sin embargo, pocos estudios han investigado estos servicios de regulación en ciudades pequeñas del Neotrópico. El objetivo de este estudio fue estimar el suministro de biomasa y el carbono secuestrado por el arbolado urbano, así como evaluar la capacidad de regulación térmica de los árboles durante la temporada más calurosa de 2021 (de diciembre de 2020 a mayo de 2021) en Puerto Carreño - Colombia. Se implementó un muestreo aleatorio a través de 200 parcelas circulares para estimar la biomasa y el almacenamiento de carbono de los árboles. Además, utilizamos 16 sensores iButton digitales ubicados en sitios por pares (sin sombra y con sombra de árboles) en ocho coberturas de suelo dentro de la ciudad para medir la temperatura y la humedad por hora durante seis meses. Encontramos que los bosques urbanos en Puerto Carreño tienen una diversidad de árboles relativamente alta y estructuras verticales complejas, mayores que las de ciudades más pobladas de la región, y un alto almacenamiento de carbono (en un rango entre 37 - 51 tC/ha). La regulación térmica de los bosques urbanos aumenta exponencialmente con la temperatura ambiente, es decir, 7,5 °C a 44 °C, mientras que 2 °C a 34,9 °C. Específicamente, durante los extremos de calor más altos, los bosques urbanos neotropicales maximizan los efectos de enfriamiento. La humedad relativa es generalmente mayor en las áreas sombreadas que en las áreas sin sombra, lo que

es aún más pronunciado durante los períodos críticos de calor. Bajo un contexto global, Puerto Carreño tiene un alto riesgo de desarrollar una combinación mortal de condiciones climáticas de temperatura y humedad. Altos índices de no confort térmico son mitigados considerablemente por los bosques urbanos por un factor de 10 durante las horas más calurosas (9 a.m. a 4:00 p.m.). Las encuestas aplicadas confirmaron que las personas perciben los efectos de bienestar de los árboles y sus servicios de regulación del clima: la sombra de los árboles y la provisión de frutas fueron los beneficios de los servicios ecosistémicos más identificados por los residentes. Nuestro estudio muestra que los bosques urbanos tropicales son una medida clave de mitigación a nivel local y global (sumideros de carbono) y adaptación (reducción del calor extremo) para combatir el cambio climático.

1. Introduction

Urban trees provide ecosystem services and multiple benefits to people across different climates and contexts. In this sense, they provide a broad suite of functions like climate regulation, carbon storage, removal of air pollutants (Cortes & Matias, 2013), reducing the risk of stormwater flow (Kato & Huang, 2021) and multiple social benefits to people including an increase of the wellbeing and social cohesion (Tavárez & Elbakidze, 2021). Currently, less is known about how the provision of ecosystem services by urban forests (UF) differs across different kinds of cities (large versus small cities, tropical versus temperate, or poor versus rich countries) since most of the literature on UF is primarily from temperate North America, Europe and now China (Escobedo et al., 2019). Thus, there is scarce available information that characterizes UF ecosystem services in cities from different parts of the globe and that considers the broad variation in their social and environmental factors (Bolund & Hunhammar, 1999; Gómez-Baggethun & Barton, 2013).

Small cities (less than 500.000 inhabitants) around the globe currently represent 59% of the world's population (United Nations, 2018), but there is scarce environmental information on these and even less for the Neotropical ones, which leads to gaps in developing and research initiatives (UN-Habitat, 2016). Despite this, these urban and periurban ecosystems, particularly in cities of the Global South, are highly complex and heterogenous but fundamental to account for in the context of meeting global biodiversity and climate goals (Dobbs et al., 2019; MacGregor-Fors et al., 2016). Although most studies of ecosystem services have focused on large cities in high-income countries (Ordóñez et al., 2020), small cities in medium-income countries present unique opportunities in terms of the implementing practices that can provide both environmental and social benefits, while minimizing negative externalities from implementing such practices (high energy use, lower pollution emissions; Frick & Rodríguez-Pose, 2018).

Global warming scenarios have predicted that changes in climate will particularly affect the tropics, low-elevation, and low-income countries and cities. Therefore, assessing ecosystem services like climate regulation in smaller and Neotropical cities in the Global South is critical due to the current scenarios of climate vulnerability that the tropics are experiencing (Mora et al., 2013). Tackling climate mitigation and adaptation challenges requires quantifying both carbon sequestration and temperature regulation which rely on the trees' basic functions of photosynthesis, and shade and evapotranspiration, respectively (Bolund & Hunhammar, 1999; Dobbs et al., 2011; Gómez-Baggethun & Barton, 2013; Pataki et al., 2011). To better inform climate change mitigation targets in neotropical cities, more integrated research is needed on not only tree carbon capture as an offset policy, but also relating to other regulation services like the cooling effect of trees and its potential role in improving human wellbeing.

1.1. Biomass and Carbon sequestration

The measurement of biomass is regularly used as a method for quantifying urban forest carbon storage but less so in tropical cities (Escobedo et al., 2015, 2016; Reynolds et al., 2017; Velasco & Chen, 2019). Besides, it is also considered an indicator of the ecological processes present in, and management of the urban forest (Dobbs et al., 2011). As reported by

Climate Action Reserve (2019), "*Trees, through the process of photosynthesis, naturally absorb CO_2 from the atmosphere and store the gas as carbon in their biomass, i.e., trunk, leaves, branches, and roots*". Due to carbon allocation across the different tree carbon pools, approximately 25% is stored in the roots (a ratio proposed mainly for trees in the tropics; (IPCC, 2006; Ma et al., 2021)), thus the measurement of biomass is usually focused on the above-ground parts (75% of the total tree biomass).

The allocation of CO_2 is affected mainly by resource availability (e.g., nutrients, light, space, water), tree size, species' strategies and soil characteristics. Bastien-Henri et al. (2010) document the effect of the dry season and degraded soils on the growth of trees in Panama, where for instance, some dry weather species tend to invest more resources into leaves and branches but fewer into stems, while in the humid zone the allocation is addressed to the stem. On the other hand, in a tropical location, the stand-level root-to-shoot ratio maintains a proportion of 0.2 (20% approximately), which is achieved through the balance between large and small roots species (Russell et al., 2010).

Methods to determine the above-ground biomass (AGB) have primarily been based on the use of destructive sampling mostly in natural forests (Chave et al., 2009). However, in the urban context this can be difficult and expensive because trees in cities are removed when the tree is mature and hazardous, probably has wood rot, or in case of construction activities (Dobbs et al., 2011; McHale et al., 2009). For this reason, other strategies that use non-destructive sampling have been broadly applied including allometric equations based on field data and information recovered using remote sensing.

An allometric equation is a relationship between biomass (or other target variables such as volume) and other easily measured variables like Diameter at Breast Height (DBH), total height, crown height and width, and/or wood density. Although most of the allometric equations for AGB are from natural forests (Chave et al., 2014), there is a lack of information for urban trees and particularly those from the tropics, which means less accurate quantification of biomass and carbon storage in urban trees (Blood et al., 2016). There are two main reasons for this: first, reduced competition for light resources in urban environments makes the trees develop the stem toward the base more rather than the crown (producing a more tapered trunk), and second, the local conditions, management and stressors of trees in cities induce to the different carbon allocation process in comparison with natural forests (McHale et al., 2009).

Remote sensing has also been used as a method to measure AGB in cities, because of the possibility of analyzing various spatial and temporal resolutions. For instance, Terrestrial (or Airborne) LiDAR (light detection and ranging) scanners have been used to acquire three-dimensional dendrometric parameters (i.e., volume or height) on standing trees with high accuracy (McHale et al., 2009; Singh et al., 2015; Velasco & Chen, 2019). Moreover, free Sentinel 2A, Landsat TM, WorldView imagery are regularly used to construct models by taking advantage of the vegetation spectral reflectance and then using vegetation indexes (VIs) like NDVI (Normalized difference vegetation index), GVI (Green Vegetation index), EVI2 (Enhanced vegetation index 2) to quantify biomass (Wu, 2019; Li et al., 2020)

But, both allometric and remote sensing derived equations require the development of statistical models using multiple regression (linear or not), correlation analysis or stepwise regression modeling, to obtain the more suitable biomass estimations, thereby avoiding overfitting and high variance inflation values (Li et al., 2020). Mueed Choudhury et al., (2019) recommend the application of Object Based Image Analysis (OBIA) of satellite images to improve the classification accuracy in urban areas minimizing the number of units to be included in the classification.

As mentioned above, AGB is a highly relevant carbon pool used to determine the quantity of carbon stored and sequestered by trees. Usually, a fraction of 0,43 – 0,49 of the total dry weight biomass is carbon according to (IPCC, 2006). Likewise, there is a conversion ratio of 3,67 used to convert carbon to CO_2 (Reynolds et al., 2017; Timilsina et al., 2014). As well, through remote sensing it is possible to make equations to estimate carbon storage (kgC) per pixel, as an example there are logarithmic equations applied by Dobbs et al. (2014) and Myeong et al. (2006), using Landsat imagery.

1.2. Temperature regulation

The influence of vegetation on urban temperatures (Bolund & Hunhammar, 1999) is also recognized as a local regulating ecosystem service (Millennium Ecosystem Assessment, 2005), which has a marked effect as a function of latitude and season (Quesada et al., 2017). Overall, while in temperate and boreal zones the change from forest cover to non-forest cover (bare land, croplands, grasslands) means a decrease in temperature due to the increase in surface albedo (Lee et al., 2011), in the tropics, these changes lead to biophysical warming. This deforestation-related warming in the tropics is mainly driven by the decrease in evapotranspiration because of the reduction in vegetation and foliar density (Perugini et al., 2017).

Furthermore, cities across the globe have been experiencing a phenomenon of temperature differences between rural (warmer) and urban areas (even warmer), which is known as the Urban Heat Island effect (UHI). This phenomenon is increased during night because the solar energy captured by the city and human activities during diurnal hours is stored in the urban construction materials, and then when the temperature of the surrounding environment drops, this heat is released arising the temperature (Doick & Hutchings, 2013). In tropical cities, the UHI differs between rainfall seasons, or even between sunny and rainy days, and is aggravated by rapid urbanization, high surface area of impervious surfaces, and suspended pollutants (most of them Green House Gases- GHG) (Da Silva et al., 2010; Md Din et al., 2014). Some authors have found that the differences between areas with and without trees can be up to 8 °C during the midday and 2°C during low radiation hours (Coronel et al., 2015; Di Leo et al., 2016; Mallen et al., 2020).

Thus, in tropical warm cities, trees have a positive impact on the reduction of the near-surface air temperature by increasing evapotranspiration while reducing the albedo surface (Hungate & Hampton, 2012) mainly in dry seasons. In this sense, the incoming radiative energy can be partly used to convert liquid water into water vapor (latent heat) instead of being released directly as heat (sensible heat), which produces lower surface air temperatures compared to a dry surface (Seneviratne et al., 2010). Also, other mechanisms imply the decrease of the albedo effect by trees compared to asphalt/bare ground (contributing to higher surface temperatures) or shading, by limiting solar penetration on impervious surfaces and windows, leading to surface cooling (Doick & Hutchings, 2013; Rahman et al., 2020).

Although an increase in evapotranspiration is related to thermal comfort, this could have an undesirable effect with the subsequent increase in humidity, especially in warm climates (Jing et al., 2013). Villadiego & Velay-Dabat (2014) and Vellei et al. (2017) found that in tropical climates, high humidity could lead to an uncomfortable conditions because it does not allow the evaporation of perspiration, a physiological mechanism that human skin uses for thermoregulation. Moreover, increasing street vegetation in the long-term can increase humidity which counteracts the decrease in temperature in climate that is humid most of the time (e.g., Singapore) (Meili, Manoli et al., 2021).

Vegetation features that facilitate the reduction of temperatures in tropical warm cities depend on traits (e.g., cover, leaf area index, leaf density), structure (e.g., height, leaf dimension, canopy height), albedo, water interception, and physiological processes (vapor pressure deficit, stomatal conductance, maximum rubisco capacity) (Rahman et al., 2020; Meili et al., 2021). The effect of these plant traits depends on the weather conditions, so for instance in a humid environment, the more moisture is the more cooling the day will be, in response to higher stomatal activity; while in drier conditions there is more regulation in this stomatal activity leading to a decrease in the transpiration rate and therefore in the cooling environment effects (Teuling et al., 2010; Gillner et al., 2015). Likewise, other factors like the wind and tree location as well as their size, planting density, management (especially soil irrigation), and species are important determinants of local cooling effects (Pataki et al., 2011).

The temperature regulation capacity in cities has been measured with different methods. Directly through the establishment of temperature/humidity data loggers under different land uses and microclimates (Coronel et al., 2015; Mallen et al., 2020); pairwise meteorological stations (Gillner et al., 2015), and indirectly through remote sensing (Di Leo et al., 2016; Guzmán, 2018; Rubiano Calderón, 2019; Wang et al., 2020) using proxy variables like land surface temperature, atmosphere temperature, and land use-cover maps. Another type of measurement is tree transpiration and its relation with other physiological traits like sap flow, stomatal conductance, wood density and total canopy leaf area, and environmental variables like radiation, precipitation, temperature and winds (Tan et al., 2020).

The effect of the thermal regulation capacity of trees in cities can be measured on people, as an example in warm tropical cities, the higher the perceived temperature, the greater the mitigating effect of high wind speeds and shaded outdoor areas (Hirashima et al., 2016; Rodríguez et al., 2016). Thermal comfort (i.e., well-being) is affected by human perception, so people who have lived in places with high temperature and humidity perceive less the negative effect of them on their activities due adaptative processes (Villadiego & Velay-Dabat, 2014). In Colombia, only 19% of 296 meteorological presented the following average thermal comfort conditions: 18 – 23 °C, 65 – 85% relative humidity, 1450 – 1800 hours per year of sunlight and height elevations between 1000 and 2000 meters above sea level (m asl); though some areas in the eastern plains, located below 1000 m asl, were within the comfort zone, because of average humidity and temperature values at certain times of the day or night (Pabón et al., 2004).

Different indices are used to measure thermal comfort, or "*the mental condition that expresses satisfaction with the thermal environment*" (ASHRAE 55[1]). These indices are used to assess the heat exchanges between the human body and its environment in terms of thermal stress. There are two main categories, direct and rational, the former is based on the combined effect between environmental variables and the latter includes human physiological effects (through metabolic rate), and behavioral (for example, clothing). A summary of these indices that applies in tropical conditions is shown in Appendix 1 (Guzmán, 2018).

Although studies of the effect of temperature and humidity, as well as heatwaves, on people have primarily focused on developed mid-latitude countries, there is evidence that deadly heat conditions also occur in low-medium income tropical countries (Gamero-Salinas et al., 2020; Geirinhas et al., 2020; Mora et al., 2017). In this regard, a recent multi-country study by Guo et al. (2018) highlighted the vulnerability of Colombia to heatwaves events under different climate change scenarios. They found that under a scenario without any adaptation to the climate change there was an increase of 2000% of the heatwave-related excess mortality in Colombia during 2031-2080 compared with 1971-2020; thus making Colombia the country most affected in the tropics and the world across the 20 countries and regions studied. This, in juxtaposition with the country's poverty conditions, could make the effects of climate change on vulnerable people more severe than expected (Campbell-Lendrum & Corvalán, 2007; Mazzone, 2020), particularly for extreme heat.

However, due to the lack of relevant information in the above studies for small cities in the Neotropics, there is a need to explore the role of urban forest management and its potential contribution to better understand how climate change scenarios affect both climate regulation and wellbeing, which are key concerns in both national and local level policies. Therefore, this study aims to determine the potential of urban trees in providing regulating ecosystem services in Puerto Carreño, a small Neotropical city in Colombia. In particular, the specific research objectives are: I. Estimate the potential biomass supply of urban trees; II. Estimate the carbon stored in its urban forest; and III. Measure the impact of urban trees on temperature regulation and subsequent human thermal comfort (i.e., well-being). Finally, the role of urban trees in mitigating the local scale effects of climate change in tropical lowland cities will be discussed.

2 Methods

2.1 Study Area

Puerto Carreño is the capital of the department of Vichada in the eastern plateau of the Colombian Orinoquia ecoregion and is located at 6º11’16” N and 67º28’ 57” W, at an altitude 51 meters above sea level. The city is in the confluence of the Orinoco, Meta and Bita river and its total area is 12.409 km^2 and has an urban area of 6 km^2. Mean annual rainfall is 2.233 mm and this more humid season is from May till to August, and the drier period is between December and March (Appendix 4, average for the period 1990 – 2018). Nevertheless, there are 1–2 months with less than 60 mm rainfall per

[1] American Society of Heating, Refrigerating and Air-Conditioning Engineers, founded in 1894.

year. Puerto Carreño holds the second maximum average temperature (36,28 °C) in the country, with the hottest period between December and March and a maximum in February; while the period of maximum low temperatures occurs from April to November, with lows in the middle of the year, in June-July (Hurtado, 2012). The annual average temperature is between 24 C° and 28 °C, which together with precipitation classifies the site as having semi-humid hot weather (Alcaldia Municipal de Puerto Carreño, 2016; IDEAM, 2018).

The urban forests in Puerto Carreño present trees distributed throughout the city in most public areas (parks, streets) and private spaces (yards, gardens). Also in the surrounding areas are some dense forests on the margins of the Meta and Bita rivers (Figure 1). In 2018, the urban zone had 27 neighborhoods and 14.974 inhabitants, of which almost 10% belonged to indigenous communities (or are recognized as indigenous); the proportions for female and male are very similar, 52,7% and 47,3% respectively, with an overall occupancy (activity that generated some income) rate of 32%. By 2015, the percentage of Unsatisfied Basic Needs was 39,11%, due to incomplete coverage in basic services such as aqueduct, sewerage, final waste disposition, electricity, housing, school absence and economic dependency; currently, the multidimensional poverty index is around 50 - 70% (Alcaldia Municipal de Puerto Carreño, 2016; DANE, 2018; Rozo et al., 2021).

Figure 1. Urban study area for Puerto Carreño, Vichada, Colombia

2.2 Biomass estimation

2.2.1 Urban tree cover Classification

Spatial cover with trees in Puerto Carreño was estimated using GeoEye satellite images hosted on Google Earth. The GeoEye images covering Puerto Carreño were taken in January of 2020 and had a ground resolution of 0,14 m. With this image, a non-supervised classification was performed using ArcMap™ 10.5 The accuracy assessment was then validated by means of a confusion matrix in which the classification obtained was compared with the control points (random distribution). The total number of points was calculated from the total number of polygons of the tree classification layer, considering the finite population calculation methodology proposed by Morillas (2004). Once the classified image was obtained, an exhaustive analysis (using the same GeoEye image) was carried out to eliminate those green areas corresponding to grass or artificial green areas (i.e. synthetic turf).

2.2.2 Plot distribution, sampling and measurements

To estimate the biomass stock in the urban forest of Puerto Carreño a random sampling was implemented. The random sampling units were based on circular plots of 400 m^2. To determine the number of plots that were necessary to characterize the study area's urban tree population, the first 20 plots (with and without trees) were measured, then the measurement error of the Diameter at Breast Height (DBH, in cm) was calculated by applying it in a random sample without replacement formula for the number of sampling units based on Sutherland (2006; Equation 1). According to the pre-sampling approach, 109 plots were required but 200 were established in total.

$$m_0 = \left(\frac{200}{Q}\right)^2 \cdot \left(\frac{S_1}{\widehat{DBH}_1}\right)^2 \cdot \left(1 + \frac{2}{m_1}\right) \qquad (1)$$

Where:

m_0: number of sample units needed in the sampling

m_1: number of sample units in the preliminary survey

DBH_1: DBH mean estimated from the preliminary sample

S_1 = DBH standard deviation estimated from the preliminary sample

Q = Error (10%)

$$m_0 = \left(\frac{200}{10}\right)^2 \cdot \left(\frac{9{,}52}{\widehat{19{,}12}}\right)^2 \cdot \left(1 + \frac{2}{20}\right) = 109\, plots$$

Plot measurements included several tree attributes (Wu, 2019): number of stems, DBH, tree height (m), crown height (m), crown diameters (polar and equatorial) and height; as well as the family, genus and species (useful to differentiate shrubs from trees joint with the phenology). To have a location of individual trees in the plot, the azimuth and the distance from the center plot were recovered. For those multi-stemmed trees (until six stems), the average DBH was calculated by the quadratic sum used by Magarik et al. (2020) and Vaz Monteiro et al. (2016) (Equation 2):

$$DBH_{MSj} = \sqrt{\sum_{i=1}^{n} DBH_{i,j}^2} \qquad (2)$$

Where:

DBH_{MS}: diameter at breast height of the multi-stemmed tree *j*

DBH_i: diameter at breast height of the stem *i* of the tree *j*

The tree cover (the proportion of urban area covered by trees) was estimated using the unsupervised classification explained in section 2.2.1, which could not detect crown overlap. Also, using the crown diameters, the crown area of each tree was calculated, from which the crown area for each plot was obtained and its equivalent on a per hectare basis (adapted from Reynolds et al., 2017).

2.2.3 Selecting allometric equations for estimating AGB

To estimate AGB, allometric equations that were developed in tropical urban areas were used (Table 1). For this, different biomass studies were reviewed from the GlobAllomeTree database (Henry et al., 2013) and Chave et al. (2014), selecting the most relevant equations based on similarity to species composition and climate conditions of trees in Puerto Carreño.

Table 1 Biomass equations. DBH: Diameter at breast height (cm), H_t: Total height (m), ρ: wood density (g/cm³), C: carbon

Equation	Formula	Fuente
3.1: Brazil	$Ln\ C = -0{,}906586 + (1{,}60421 \times \ln DBH) + (0{,}37162 \times \ln H_t)$	Brianezi et al., 2013
3.2: Brazil (branches)	$Ln\ C = -2{,}052673 + (1{,}89903 \times \ln DBH) + (0{,}24156 \times \ln H_t)$	
3.3: Pantropical	$AGB = 0{,}0559 \times (\rho DBH^2 H_t)$	Chave et al., 2014
3.4: Medellin	$Ln\ AGB = -1{,}00638 + (0{,}78984 \times \ln(DBH^2 H_t \rho))$	In prep.
3.5: Palms	$Ln\ C = -4{,}46988 + (1{,}99082 \times \ln DBH) + (1{,}06420 \times \ln H_t)$	Brianezi et al., 2013

Equations 3.1 and 3.2 were used to calculate total and per tree components (crown and stem) to better characterize tree biomass components and their use for wood waste feedstock. Equation 3.3 was developed in a pantropical context, while Equation 3.4 was developed in another Colombian city, Medellin. For palms, equation 3.5 was used. Once the aboveground biomass was determined, it was multiplied by the conversion factor of 0,47 which represents the quantity of carbon in the dry biomass and then by 3,67, the conversion rate from C to CO_2e (IPCC, 2006; IPCC, 2018). The relation between total tree biomass (calculated with 3.1, 3.3 and 3.4), average DBH, average height, total crown area, wood density and number of trees per species was evaluated by applying the Spearman correlation coefficient. Using the variables with a higher correlation coefficient with biomass, non-linear equations were used to identify the best predictor of urban tree biomass using the Akaike Information Criterion (AIC; Gotelli & Ellison, 2013). Finally, confidence and prediction intervals at a confidence level of 95% were calculated for the best predictor, using the *propagate* and *tidymodels* packages from the R language (Spiess, 2018; Kuhn & Wickham 2020).

2.3 Temperature regulation

2.3.1 Thermal climate and meteorological context

To characterize the meteorological context of Puerto Carreño, data from at least the last ten years of temperature, precipitation, humidity, sun hours per day and cloudiness were collected from the *Aeropuerto Puerto Carreño* IDEAM meteorological station (located in the urban zone, available at http://dhime.ideam.gov.co/atencionciudadano/). Data were then used to obtain the diurnal cycles to better identify the occurrence of maximum and minimum data, as well as to develop annual histograms using a range of 10 days to explore the relationships between variables (adapted from Guzmán, 2018). Such information on climatic variation during the day was used to determine the appropriate season and time period for data collection: December 2020 to May 2021 given the high presence of hot extremes (Appendix 4, Figure).

2.3.2 In situ sampling of air temperature and humidity

Between December 2020 and May 2021, 16 iButton® DS1923 humidity and temperature sensors were installed in seven sectors of the urban zone searching to characterize different conditions that could affect microclimate (i.e. trees, grass, impervious covers; Mallen et al., 2020; Meili et al., 2021). Temperature monitoring accuracy was ±0.0625 ◦C and ±0.04% for relative humidity. The sensors were protected from rain and direct solar radiation using a corrugated plastic structure covered with a foil insulation tape assuring the exchange of air and located 1,5 m above the ground. All the devices were arranged in pairs and did not exceed a distance between them of 100 m. One sensor had sun exposure (unshaded), and another was placed beneath the tree crown in the mid radius of the canopy, thus avoiding the influence of direct solar radiation.

Sensors were selectively installed in representative, accessible, protected sites to keep them accessible, safe, and to avoid vandalism, in seven different sectors of the study area and 1 peri-urban site that is currently consolidating itself as a neighborhood: Las Granjas (Figure 2). To identify tree species in sensors located under a tree's canopy, a 400 m² biomass plot (section 2.2.2) was established using as center the datalogger position. Each sensor collected hourly data for five months and was downloaded five times during the period studied. According to the land cover present 30 m around the sensors, four different ground cover type were classified as shown in Table 2 (third column).

Table 2 Location of temperature and humidity sensors

Site	Coordinates	Ground cover types	Land cover category
Las Granjas	67°30'15,074"W 6°11'6,238"N	Grass and bare ground and large trees	Peri-urban and grass
CJEG School	67°29'49,463"W 6°11'10,295"N		
CH	67°29'5,175"W 6°11'47,698"N	Asphalted road, grass and large trees	Dense trees
FO	67°28'52,155"W 6°10'53,56"N		
CMI School	67°29'22,864"W 6°10'58,871"N	Concrete pavements, asphalted road, some green (trees and grass)	Impervious
Sena	67°29'7,445"W 6°10'59,728"N		
Punta Laja	67°28'45,302"W 6°10'39,512"N	Asphalted road, bare ground and some green (trees)	Scattered trees
Santa Teresita	67°28'41,747"W 6°11'26,711"N		

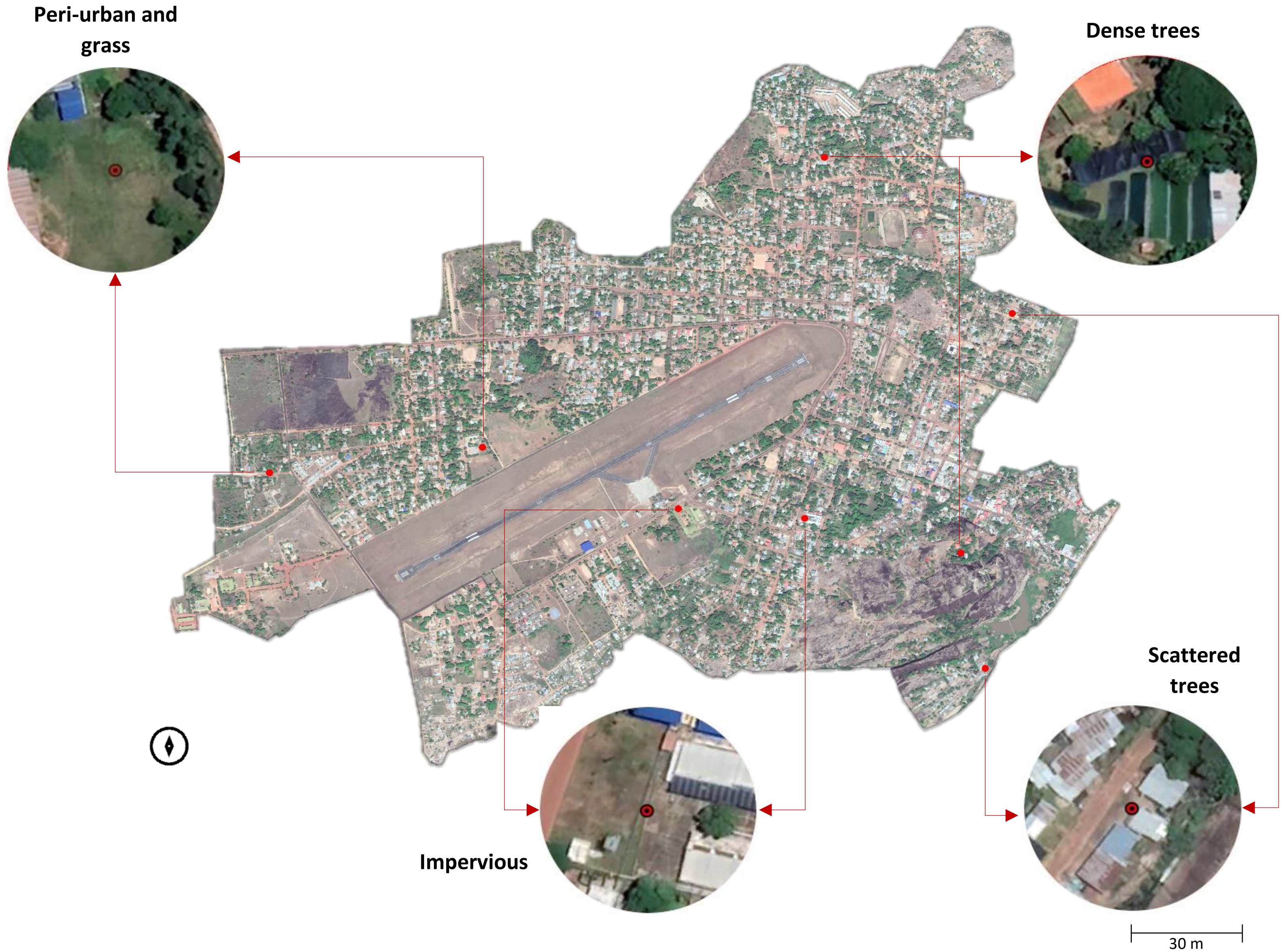

Figure 2 Location in Puerto Carreño and land cover 30 m around the sensors

2.3.3 Pre-treatment of the data

During the sampling period, from December 2020 to March 2021, two of the sensors located under trees in Santa Teresita's neighborhood and FO were vandalized (names come from Table 2), and thus did not collect data after December and March respectively. In these cases, only the acquired data was included in the analysis. Also, in March 2021, the sensor located under sun exposure in the CJEG School had signs of a bird nest, so the data was filtered to detect outlier temperatures. Accordingly, these atypical measurements were adjusted as shown in Appendix 2.

2.3.4 Data analyses

Using the complete dataset, significant differences in temperature and humidity per month in each sensor (between shaded and unshaded conditions) were tested using the Welch t-test (α = 0,05). Normality in the data was assumed because of the quantity of data per month (>100 records), and correction for unequal variances was done when necessary, using Fisher's test ($p>0,05$). Also, temperature and humidity in sensors at the same shading conditions, exposed and shaded, were compared following the same steps. Comparisons made in the same shade conditions were: Scattered trees – Periurban and grass, Scattered trees – Dense trees, Impervious – Periurban and grass, Impervious – Dense trees, Scattered trees – Impervious, and Dense trees – Periurban and grass.

Diurnal cycles for temperature and relative humidity were obtained through an average of the hours for all sensors each month. The data set also characterized temperature and relative humidity changes during the day, as well as the difference between each pair of sensors: sun exposure and under tree cover. Also, we calculated the effect of temperature and relative humidity of unshaded sensors on the temperature difference using a polynomic order 2 nonlinear model using the *nlstools* library in R language v.4.0.1 (equation 4):

$$T_{diff} = a \cdot \left(\beta_{exp}\right)^2 + b \cdot \beta_{exp} + c \qquad (4)$$

Where:

T_{diff} = difference of temperature between sun exposure and shade for the same hour for each sensor

β_{exp} = Temperature or relative humidity of the unshaded sensors (sun exposure)

a and b = slopes

c = intercept

To show humidity and temperature conditions in Puerto Carreño between December 2020 and May 2021 that could increase lethality risk, we used the 95% Support Vector Machine (SVM) deadly threshold proposed by Mora et al. (2017) with the daily average for both unshaded and shaded sensors. This global analysis employed "*documented lethal heat* *events to identify the climatic conditions associated with human death and then quantified the current and projected occurrence of such deadly climatic conditions worldwide*.". Thus, this threshold differentiated lethal from not lethal heat events of different cities worldwide (during documented cases of excess mortality) and depicted the climatic thresholds of temperature and humidity over which an event can lead to a significant increase in mortality risk.

We then used Thom's discomfort index (DI; Thom, 1959) to relate the temperature and humidity data to a human discomfort category. Specifically, we calculated DI for each sensor, using both hourly temperature and relative humidity in sun exposure sensors (due to its supposed thermal discomfort) and under tree-shaded sensors. This index was used since most rational and direct indices (Appendix 1) need variables that are difficult and expensive to collect in these types of contexts (vapor pressure, wet-bulb temperature, globe temperature, wind speed, mean radiant temperature). We calculated DI using equations 5 and 6.

$$DI_{exp} = T_{exp} - 0{,}55 \cdot (1 - 0.01 \cdot RH_{exp}) \cdot (T_{exp} - 14{,}5) \qquad (5)$$

$$DI_{shd} = T_{shd} - 0{,}55 \cdot (1 - 0.01 \cdot RH_{shd}) \cdot (T_{shd} - 14{,}5) \qquad (6)$$

Where:

DI_{exp}: discomfort index for unshaded sensors

DI_{shd}: discomfort index for sensors under tree's shadow

T: ambient temperature in °C (*exp*: unshaded, *shd*: under tree shade)

RH: relative humidity expressed as a percentage.

Thom's (1959) DI index originally uses four different classes, however, in a very tight range under which most of the time the weather in Puerto Carreño would be uncomfortable. Therefore we applied the classification proposed by Da Silva et al., (2010) for a tropical city in Brazil: ***1.*** No discomfort: DI ≤ 21; ***2.*** Uncomfortable: 21 < DI ≤ 27 (Less than 50% of the population feels discomfort: 21 < DI ≤ 24; More than 50% of the population feels discomfort: 24 ≤ DI ≤ 27); ***3.*** Most of the population suffers discomfort: 27 ≤ DI ≤ 29; and ***4.*** Discomfort is very strong and dangerous: 29 < DI ≤ 32 and ***5.*** State of medical emergency: DI > 32. We then used these classes/ranges to characterize DI between sensors in unshaded versus shaded sites; thus, describing the effect of the urban trees on the comfort perceived by people.

2.3.5 Thermal comfort survey

The effect of measured data and the DI on the cooling effect of trees as perceived by people was assessed by using an in-person intercept survey (Appendix 3). The survey instrument was conducted on 140 pedestrians across three different areas in Puerto Carreño: downtown, in neighborhoods, and at the port on the Orinoco River. The survey took place during January and February 2021, and during the workday hours of 8:00 a.m. to 4:30 p.m. The survey instrument was divided into three parts: the first collected survey location (coordinates), demographic data from the population (e.g., age, gender, educational level, origin, time living in Puerto Carreño), observational data (clothing, people position), time of day and if the place was shaded or not because of trees, shelter, or both. The second part assessed the perception of the weather at the time of the survey and their degree of acceptance and tolerance for the weather condition they were experiencing. Finally, the third part of the survey assessed the perceived importance of trees to respondents. This survey was designed based on previous research (Yang et al., 2013; Md Din et al., 2014; Villadiego & Velay-Dabat, 2014) and the ASHRAE Standard (2004).

During the second part of the questionnaire, we focused on respondents' perceptions of sensation, acceptance, temperature tolerance, relative humidity, wind speed and solar radiation. Since Puerto Carreño tropical climate does not have a 'cold' winter period, a modified sensorial scale of seven points was used to measure thermal perception. Specifically, 4 is very hot, 3 is hot, 2 is warm, 1 is slightly warm, 0 is neutral, -1 is slightly cool and -2 is cool. We then used a five-point Likert scale to measure the degree of comfort and tolerance to the weather: 0, perfectly acceptable and 1, slightly comfortable or tolerable; 2, Uncomfortable or Very hard to accept; 3 very uncomfortable or difficult to accept; 4, Extremely uncomfortable or intolerable.

Relative humidity (RH), wind speed (WS) and solar radiation (SR) were also measured using a five-point Likert scale, where -2, means any humidity/wind/solar radiation; and 2, too much humidity/wind/solar radiation, with 0 normal or average humidity/wind/solar radiation. The thermal preference was assessed using the McIntyre symmetrical scale (1980) where -1, prefer cooler; 0, no change and 1, warmer. Finally, we asked if the respondent accepted (0) or not (-1) the current weather conditions. Also, we asked respondents to identify the least pleasant of the following 4 conditions at the time of the survey: temperature, solar radiation, wind speed and humidity.

In the third part of the survey instrument, people's awareness about the relationship between some regulation ecosystem services (i.e., temperature mitigation) and trees was assessed, as well as the respondents' opinion regarding the presence of trees in the city. Some open-ended questions were asked to obtain a more complete range of answers such as: Do you have trees near your house? If not, do you want to have it and why? Have you experienced excessive heat at night? What are the benefits (services) and damages (disservices) of trees in the city?

Contingency tables (Chi-square test, $p < 0,05$) were used to test for significant differences in thermal comfort (survey question 2) due to gender, education level, age, shaded conditions during the survey, and respondent perceived: solar radiation, wind and humidity. Then, using the variables with a significant relationship with thermal comfort ($p < 0.05$), a correspondence analysis (Díaz & Morales, 2012) was carried out to show the influence of each level of the variables on the comfort expressed by the respondents. A contingency table was used to determine if night-time heat was related to the presence/absence of trees adjacent to the respondent's houses, (Chi-square test, $p < 0,05$) using R language 4.0.1.

3 Results

3.1 Biomass stock and associated carbon content

The results of the evaluation of the accuracy of the tree cover classification are shown in Table A3. A total of 2,544 polygons with tree cover were counted according to the classification, and 334 points were needed to sample and validate the accuracy of the classification. These 334 points were randomly distributed in the urban area of Puerto Carreño. The overall accuracy of the classification using the confusion matrix was 93,4% and a kappa parameter of 80,3%. According to this classification the urban tree cover is 18% and represents 1,17 km^2 without accounting for overlapping crowns. In terms of tree crowns, the trees sampled have around of 35,35 m^2 of crown area which scaled to the city area is almost 2,8 km^2, assuming no overlapping crowns, or 44% of the city. This equates to having potentially 78 m^2 of tree cover for each inhabitant.

In general, 79 plots had at least one tree, and 360 trees were measured belonging to 66 tree and shrub species (56 to species and 10 to genus), three species of palms, and one unidentified species. The most abundant species were *Mangifera indica* (mango; 96 trees) and *Andira surinamensis* (pilón; 52 trees); the third species with more trees was *Melicoccus bijugata* with twelve trees, the other species registered between 11 and one tree (28 species). At least 15 species were fruit trees growing in house yards and streets, indicating an important source of food for the homeowners and pedestrians. Palms were not so frequent as trees, just in eight of the 200 plots measured, represented by five species and 11 palms, being the most common *Elaeais guineensis* known as oil palm.

At least three different vertical strata were identified: 1. Large mature trees with DBH and height greater than 80 cm and 10 m respectively (19); 2. mature trees: 10 cm < DBH < 80 cm (311); and 3. young trees/shrubs: 5 cm < DBH < 10 cm (30). The majority of measured trees (93%) have spreading crowns that favored understory plant growth. Thus, it was common to find young trees and shrubs (shade-tolerant, i.e., *Neea ignicola, Theobroma cacao, Annona squamosa*, *Phyllanthus sp*.) growing under these large mature trees (i.e., *Mangifera indica, Samanea saman*). Such a condition indicates an urban forest with a complex vertical structure and is typical of most tropical forest structures. Although this structure is very common in vacant lots and parks (due to the space necessary for the development of large canopies), it is possible to find it on sidewalks and house yards as well

The average aboveground biomass per plot is estimated between 3.80 and 4.33 kg, which is equivalent to an average of between 79 and 108 tons of C/ha (Table 3). The carbon storage per tree cover area is between 4,1 and 8,5 kgC/m^2. The overall carbon storage per tree is in the 337-461 kgC range, using the tree allometric equations of Table 1 (equations 3.1, 3.3 or 3.4). In palms, the AGB range was 2,7 kg to 601 kg in a young *Socratea exhorriza* and a mature *Elaeais guineensis* respectively.

The top species that store the most carbon were the mango tree (*Mangifera indica*), pilón (*Andira surinamensis*) and carob tree (*Hymenaea courbaril*), those species accounted for at least 60% of the total AGB in the plots. More than the abundance (number of trees, Spearman ρ = 0,57 – 0,63), the size of the trees had a great influence on the AGB value, as in the case of the carob tree, which was not an abundant species (7 trees in the sample) but with mature trees of great diameters and heights. Also, that was the situation for other species such as *Copaifera officinalis* (10 trees), *Phitecellobium dulce* (10 trees), and *Samanea saman* (4 trees) the next three species with the highest amount of carbon stored.

Table 3 Summary of stocked biomass using different equations (t: tons, DM: dry matter, C: carbon)

Parameter	**Eq Brazil**	**Eq Pantropical**	**Eq Medellin**
Average dry ABG (kg/plot)	3.804	4.334	3.169
Standard error (kg/plot)	105	177	98
t(DM)/ha	95	108	79
tC/ha	45	51	37

From the measured variables those that had more relation with biomass were DBH (Spearman ρ = 0,81 – 0,84), tree height (Spearman ρ = 0,69 – 0,74) and crown area (Spearman ρ = 0,72 – 0,75). Although wood density was used in two of the equations to estimate biomass it was not a variable that can be characterized independently (Spearman ρ = 0,15 – 0,23, non-significative). From the three variables with a higher Spearman correlation coefficient (Spearman ρ), the best predictor to estimate tree biomass in Puerto Carreño was the DBH (Table 4), it applies mainly to trees with diameters smaller than 80 cm where most of the biomass values were amid the prediction interval at 95% of confidence using whatever of the three equations of Table 1 (equations 3.1, 3.3 or 3.4) (Figure 3).

Table 4 Biomass equations using each variable measured in this study, determination coefficient (R^2) and Akaike criterion (AIC)

Equation	**R^2**	**AIC**
$\mathrm{B} = 0{,}44\times(\mathrm{DBH})^2 - 14{,}02$	0,89	15.848,21
$\mathrm{B} = 7{,}42\times(\mathrm{Height})^2 - 262{,}64$	0,70	16.946,78
$\mathrm{B} = 6{,}07\text{e-}06\times(\mathrm{Crown\ area})^2 + 799.69$	0,50	17.400,45

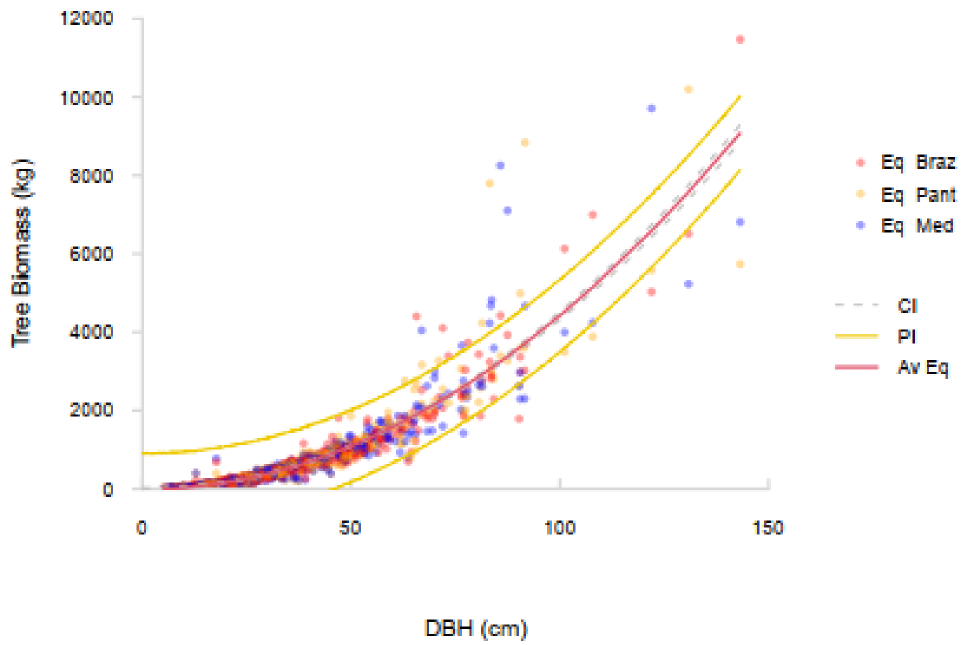

Figure 3 Individual tree dry weight biomass according to diameter at breast height (DBH).

Note Eq, equation; Braz, Brazil; Pant, Pantropical; Med, Medellín; CI, confidence interval; PI, prediction interval; Av Eq, Average DBH equation from this study presented in Table 4.

3.2. Temperature regulation

3.2.1. Thermal climate and meteorological context

There was a monomodal precipitation pattern marked by a single wet season during from April to October and a dry season between November and March (see Supplementary Figure S2. b). During the dry season, the values of temperature and solar brightness are the highest, reaching extreme values (Supplementary Figure S2. a y d). Based on data from previous decades, we found that days with extreme temperatures greater than 37 °C and 38 °C were more frequent in the recent decade (2010-2019) than in the previous decade (2000-2009) (Supplementary Figure S2. a). Likewise, we find that wet days (days with precipitation > 1 mm) increased by 9 days between 2000 and 2018, while the precipitation amount during the consecutive rainiest days of the year increased by 40-60 mm between 2000 and 2018 (see Supplementary Figure S2. b). 2020 in particular was a hot year as indicated by data showing that until October 2020, 75% of the days had temperatures above 30 °C and 16% of days with temperatures above 33 °C, which is very close to the 90th percentile. See Figures in Appendix 4 for temperature, rainfall, relative humidity, hours of sun per day and cloudiness for these years.

3.2.2. In situ sampling of air temperature and humidity

Monthly patterns and temperature regulation

During the hottest period, December 2020 to March 2021, average air temperatures were 29,5°C and 28,9°C in unshaded and shaded sensor sites, respectively. During the onset of the rainy period, April to May 2021, average air temperatures registered were 28,4°C and 27,7°C in unshaded and shaded sensors respectively. Overall, the months with a higher frequency of hot days (i.e., “hot” is used for temperature higher than 90th percentile: 34,5 °C) were February (16%) followed by March (14%), with extreme temperatures up to 43 °C. The hottest daily time period was between 12:00 p.m. – 3:00 p.m., with almost 71% of the temperatures classified as hot, notably higher than the time periods before and after 12:00 p.m. (15%) and 3:00 p.m. (14%) respectively. There were no hot temperatures before 7:00 a.m. and after 5:00 p.m. The lowest temperature, 22°C, was registered between 4:00 a.m. and 6:00 a.m. only in sensors located in periurban and grassland zones in both shaded and unshaded sensors.

Regardless of the sensor being shaded or exposed to the sun, the relative humidity averaged 65% to 81% during the hottest period, from December 2020 to March 2021, and at the beginning of the rainy period, April and May 2021, respectively. Over February and March 2021, the relative humidity was lowest (less tan 67%) compared with the rest of the months studied, which was more noticeable in unshaded sensors except for one of the sensors located in the grass (CJEG School, Table 5). Once the rains started in April 2021 the relative humidity rose rapidly (greater than 75%). Overall temperature and relative humidity showed a contrasting pattern, where the hottest months are those with minor relative humidity. With few exceptions, relative humidity was higher in shaded relative to unshaded land use-cover types (Table 5)

Comparisons in unshaded versus shaded sensors between the different covers showed there was a difference in temperatures based on the surrounding environment. Thus, significant temperature differences (greater than 1,79%) were found between covers with more trees (periurban and grass, and dense trees) and less green (Scattered trees and impervious) both in shaded and unshaded sensors (up to 6,79%). Higher differences in temperature between covers were achieved in March 2021 for unshaded sensors (1,37 °C), while in shaded sensors significant differences happened during December 2020 and April 2021 (0,86 °C and 0,91 °C respectively). Regarding humidity, differences were significant in most of the cover comparisons in both shaded and unshaded sensors, except for those between covers with fewer trees (Table 6).

Tree biomass was evaluated in each sensor under shade using the same plots for the biomass section 3.1 (circular plots of 400 m²). The average values (obtained from equations 3.1, 3.3 and 3.4 in Table 1) oscillate between 1.100 kg and 13.000 kg per plot. The highest value was found in the FO sensor whose cover was dense trees, while the lowest was recorded in a sensor located in an impervious cover around.

Table 5 Average temperature and relative humidity per month collected by each sensor.

COVER	SENSOR	SUN/ SHADE	TEMPERATURE °C						RELATIVE HUMIDITY %					
			DEC 20	JAN 21	FEB 21	MAR 21	APR 21	MAY 21	DEC 20	JAN 21	FEB 21	MAR 21	APR 21	MAY 21
Periurban and grass	Las Granjas	*Sun*	28,6	28,2	29,5	29,5	28,6	27,7	73,9	71,1	62,4	65,6	78,9	86,7
		Shade	27,7	27,6	29,1	28,9	27,8	27,0	75,2	72,4	62,9	66,3	80,6	88,7
		Difference	***0,91****	***0,63****	***0,47****	***0,59****	***0,74****	***0,71****	***-1,33***	***-1,29***	***-0,54***	***-0,67***	***-1,74***	***-2,04****
	CJEG School	*Sun*	28,4	28,1	29,6	<u>29,4</u>	<u>28,3</u>	<u>27,5</u>	75,9	73,8	63,8	<u>67,0</u>	<u>80,4</u>	<u>88,2</u>
		Shade	28,3	28,0	29,4	29,2	28,1	27,3	72,3	70,0	61,2	64,7	77,9	85,9
		Difference	***0,12***	***0,18***	***0,22***	***0,19***	***0,18***	***0,25***	***3,64****	***3,78****	***2,65****	***2,30****	***2,44****	***2,27****
Dense trees	CH	*Sun*	28,8	28,5	30,1	29,8	28,6	27,8	72,5	70,2	60,9	64,3	77,8	85,2
		Shade	28,0	27,8	29,3	29,0	27,7	26,8	73,6	70,6	61,7	65,5	79,9	87,7
		Difference	***0,72****	***0,67****	***0,80****	***0,87****	***0,95****	***0,99****	***-1,05***	***-0,41***	***-0,79***	***-1,22***	***-2,06****	***-2,52****
	FO	*Sun*	29,0	28,6	30,0	29,8	28,7	27,8	71,0	68,7	60,3	63,9	76,3	84,3
		Shade	28,5	28,3	29,7	29,4	ND	ND	71,5	68,6	60,0	61,8	ND	ND
		Difference	***0,51****	***0,30***	***0,34***	***0,30***	ND	ND	***-0,29***	***0,16***	***0,30***	***0,11***	ND	ND
Impervious	Sena	*Sun*	29,3	28,9	30,3	30,0	28,9	28,1	67,5	66,1	58,0	62,2	75,1	82,0
		Shade	29,0	28,5	29,8	29,5	28,4	27,6	69,0	67,0	59,1	63,0	76,4	84,0
		Difference	***0,35***	***0,46****	***0,54****	***0,43****	***0,50****	***0,48****	***-1,48***	***-0,92***	***-1,04***	***-0,84***	***-1,29***	***-2,05****
	CMI School	*Sun*	29,1	28,9	30,4	30,1	28,9	27,9	68,5	66,3	58,0	62,1	75,5	83,5
		Shade	28,7	28,3	29,8	29,5	28,4	27,4	69,4	67,4	59,1	62,8	75,9	83,9
		Difference	***0,43****	***0,58****	***0,62****	***0,59****	***0,52****	***0,48****	***-0,88***	***-1,19***	***-1,10***	***-0,72***	***-0,44***	***-0,43***
SCATTERED trees	Punta Laja	*Sun*	29,9	29,4	31,1	31,2	29,6	28,6	67,7	66,3	58,1	60,4	75,5	84,3
		Shade	29,0	28,5	30,0	29,7	28,6	27,5	67,5	66,5	58,5	62,2	75,1	84,0
		Difference	***0,90****	***0,85****	***1,19****	***1,46****	***0,99****	***1,11****	***-0,69***	***-0,24***	***-0,47***	***-1,87****	***0,35***	***0,29***
	Santa Teresita	*Sun*	29,6	29,2	30,7	30,5	29,3	28,2	68,9	66,7	58,3	61,8	75,4	83,8
		Shade	28,2	ND	ND	ND	ND	ND	72,6	ND	ND	ND	ND	ND
		Difference	ND	ND	ND	ND	ND	ND	ND	ND	ND	ND	ND	ND

Values in gray correspond to the same land-use cover (Table 2) ND: No Data due to vandalization of the sensor. Underlined values belong to the "nested" sensor.

*means significative difference t-test $p<0,05$. DEC20: December 2020, JAN21: January 2021, FEB21: February 2021, MAR21: March 2021, APR21: April 2021 and MAY21: May 2021

Table 6 Differences in temperature and relative humidity per month between covers under same shade condition (Sun and Shade).

COMPARISONS BETWEEN COVERS	SUN/ SHADE	TEMPERATURE °C						RELATIVE HUMIDITY %					
		DEC 20	JAN 21	FEB 21	MAR 21	APR 21	MAY 21	DEC 20	JAN 21	FEB 21	MAR 21	APR 21	MAY 21
Difference between Scattered trees – Periurban and grass	*Sun*	1,15*	1,08*	1,32*	1,37*	0,97*	0,77*	-6,15*	-5,88*	-4,97*	-5,22*	-4,19*	-3,39*
	Shade	0,77*	0,76*	0,71*	0,63*	0,57*	0,77*	-4,35*	-4,61*	-3,54*	-3,27*	-4,17*	-3,28*
Difference between Impervious – Periurban and grass	*Sun*	0,75*	0,73*	0,78*	0,55*	0,44*	0,37	-6,79*	-6,24*	-5,11*	-4,18*	-4,34*	-4,69*
	Shade	0,86*	0,61*	0,54*	0,43*	0,39*	0,37*	-4,50*	-3,94*	-2,99*	-2,59*	-3,13*	-3,33*
Difference between Scattered trees – Dense trees	*Sun*	0,70 *	0,74*	0,87*	1,04*	0,78*	0,60*	-2,72*	-2,96*	-2,47*	-3,05*	-1,61	-0,71
	Shade	0,39	0,50*	0,49	0,64*	0,91*	0,64*	-2,58*	-3,07*	-2,35*	-2,93*	-4,76*	-3,65*
Difference between Impervious – Dense trees	*Sun*	0,3	0,38	0,33	0,22	0,25	0,19	-3,38*	-3,33*	-2,62*	-2,01*	-1,76	-2,00*
	Shade	0,53*	0,35*	0,32	0,43*	0,73*	0,70*	-2,95*	-2,39*	-1,79*	-2,25*	-3,71*	-3,70*
Difference between Scattered trees – Impervious	*Sun*	0,39	0,36	0,54	0,81	0,53	0,41*	0,71	0,36	0,15	-1,04	0,15	1,29
	Shade	-0,1	0,15	0,16	0,2	0,18	-0,06	-0,02	-0,67	-0,56	-0,68	-1,05	0,05
Difference between Dense trees – Periurban and grass	*Sun*	0,44*	0,35	0,45	0,33	0,19	0,17	-3,32*	-2,91*	-2,49*	-2,18*	-2,58*	-2,69*
	Shade	0,38*	0,26	0,22	0	-0,34*	-0,34*	-1,72	-1,54*	-1,19	-0,34	0,58	0,37

Values in gray correspond to the same shade condition. *****Significative difference t-test p<0,05. DEC20: December 2020, JAN21: January 2021, FEB21: February 2021, MAR21: March 2021, APR21: April 2021 and MAY21: May 2021

Hourly patterns and temperature regulation

During the daytime, there is a difference in both temperature and humidity in unshaded places (Figure 4a - 4d) or directly under sun exposure. Where there are fewer trees, the greater the effect of the trees in terms of temperature regulation (Figure 4l), likewise the fact that there are fewer trees and green covers generates a greater difference in the relative humidity compared to those where natural covers are more abundant (Figure 5i - 5l). The highest difference for both temperature and relative humidity was expressed during the critical period of the day, 12:00 p.m. – 3:00 p.m. During this time, the average temperature differences between unshaded and shaded sensors range from 1,94 ° C in environments with green covers and trees, up to 3,97 ° C in impervious and less vegetated spaces, showing the influence of trees in highly urbanized spaces, especially during February and March 2021. At the same time, humidity decreased, achieving up to a 10% of difference between unshaded and shaded sensors in places with less presence of trees (Figure 5l).

During night-time, microclimate was homogeneous in the different covers with a small range of amplitudes (closer to cero) compared with those at daytime. However, there is a contrasting effect of tree cover on temperature and relative humidity. Specifically shaded sensors located under trees held higher temperatures (up to 40°C) than did unshaded sensors, while humidity decreased in shaded sites (i.e., under trees) but only during the hottest months (February and March, (up to 10%) and increased during the beginning of the rainy season, due to an excessive humidity in the environment between tree crowns and ground surfaces (Figures 4 and 5).

Regulation of temperature due to the trees and measured through the difference in temperature between the sensors without shade and shaded and air temperature and relative humidity, was found to have an opposite effect. Figure 6a. shows that as the ambient temperature is higher, the mitigation of heat by the trees is exponentially greater. Thus, when the environment reached a daily temperature of 44,0 °C (maximum daily exposure temperature registered), the average mitigation due to trees was 7,5 °C while at 34,9°C (mean daily exposure temperature registered), the thermal regulation is 2°C. While in the case of humidity (Figure 6b.), there are two conditions, one in which a high relative humidity entails lower mitigation of heat, (i.e., heat or suffocation), and another in which a higher relative humidity in the environment generates a decrease in temperature due to rain events or an increase of the cloudiness (Figure 6 and Table 7). Nevertheless, it seems there is a limit under 28 °C and relative humidity greater than 60% in which the thermal regulation by trees is not as effective as in extreme conditions (Figure 6).

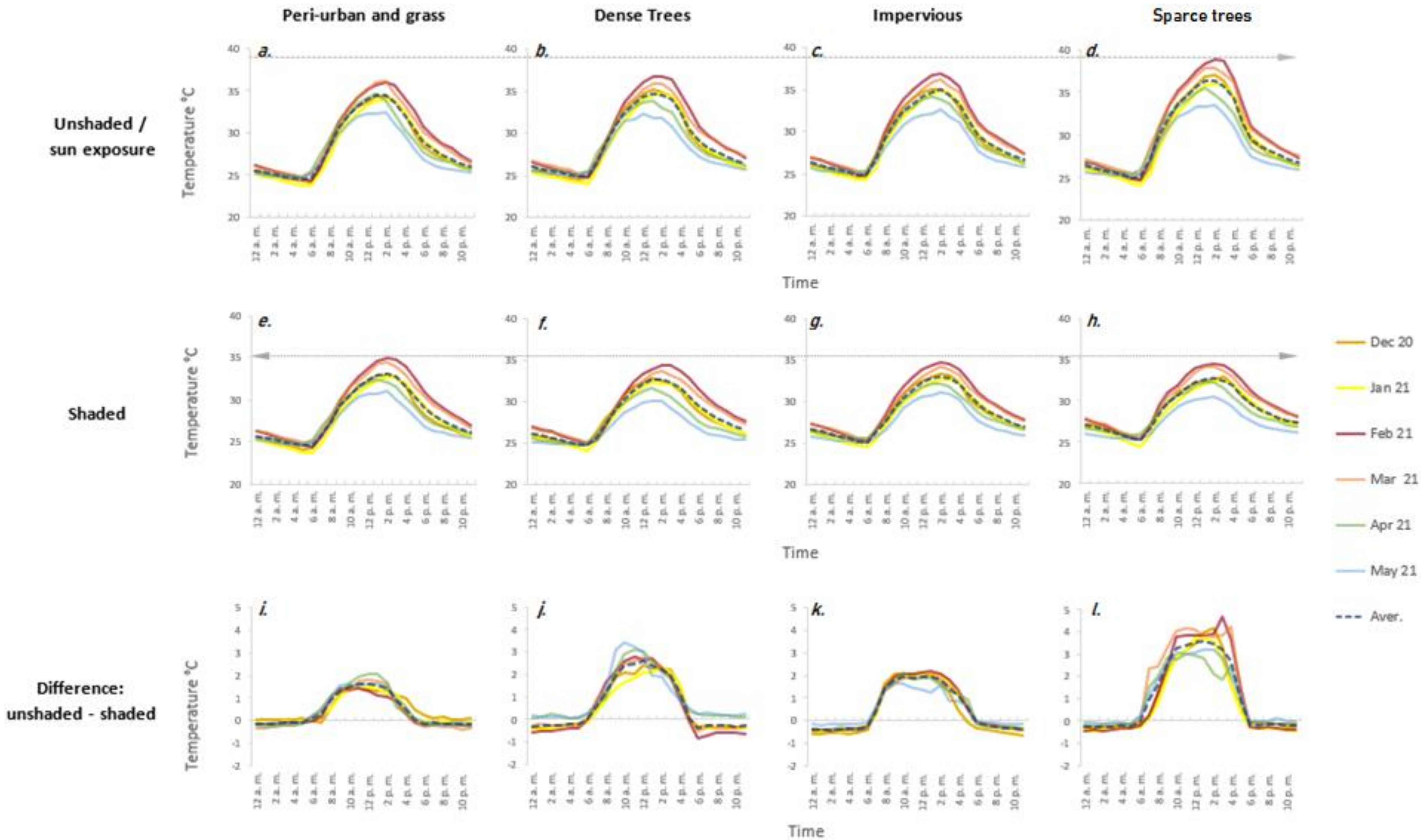

Figure 4 Hourly temperature per month (during December 2020 and May 2021) and cover.

Upper panels: Unshaded sensors, middle panels: shaded sensors, lower panel: difference between unshaded and shaded sensors.

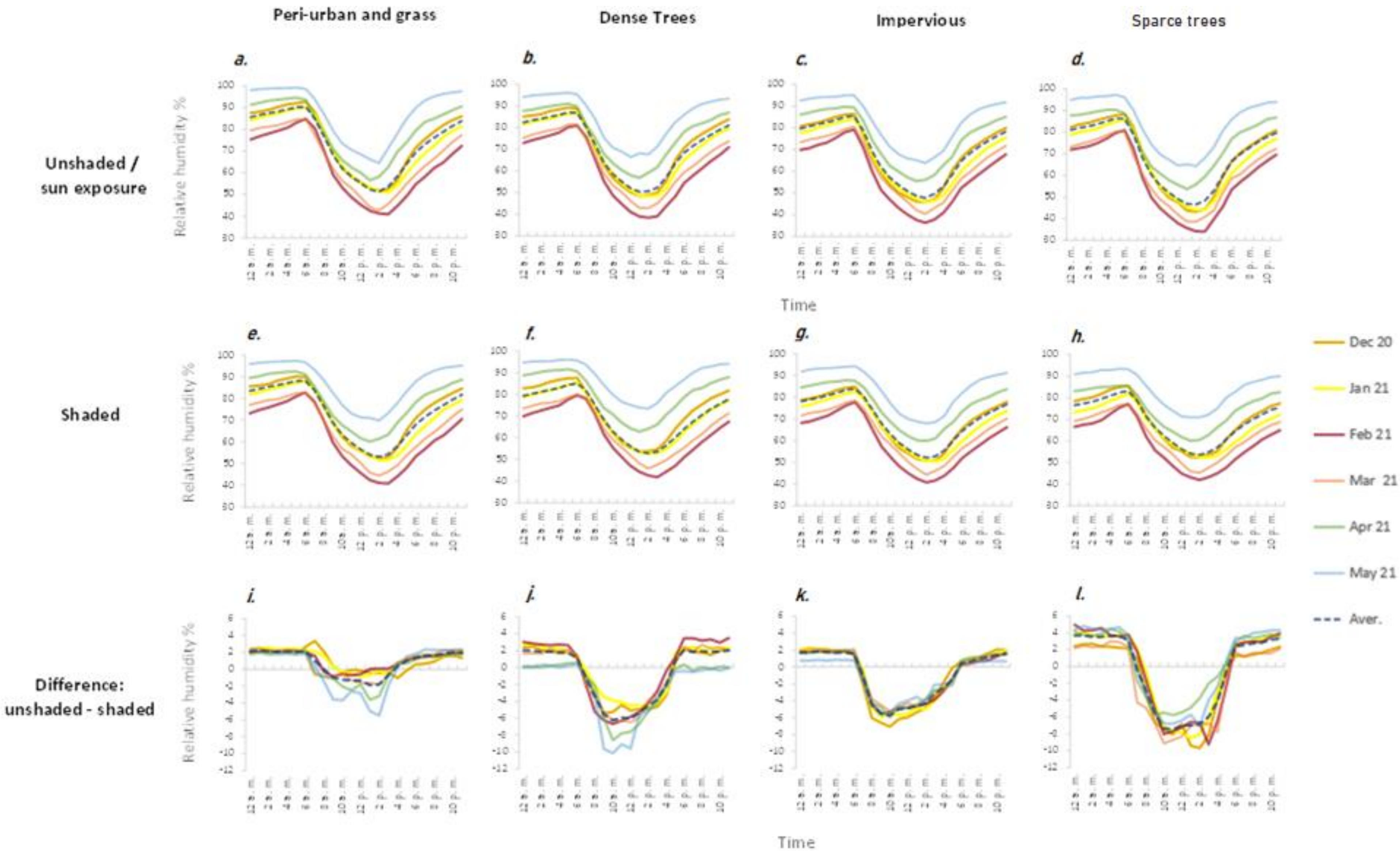

Figure 5 Hourly relative humidity per month (during December 2020 and May 2021) and cover (columns).

Upper panels: Unshaded sensors, middle panels: shaded sensors, lower panels: difference between unshaded and shaded sensors.

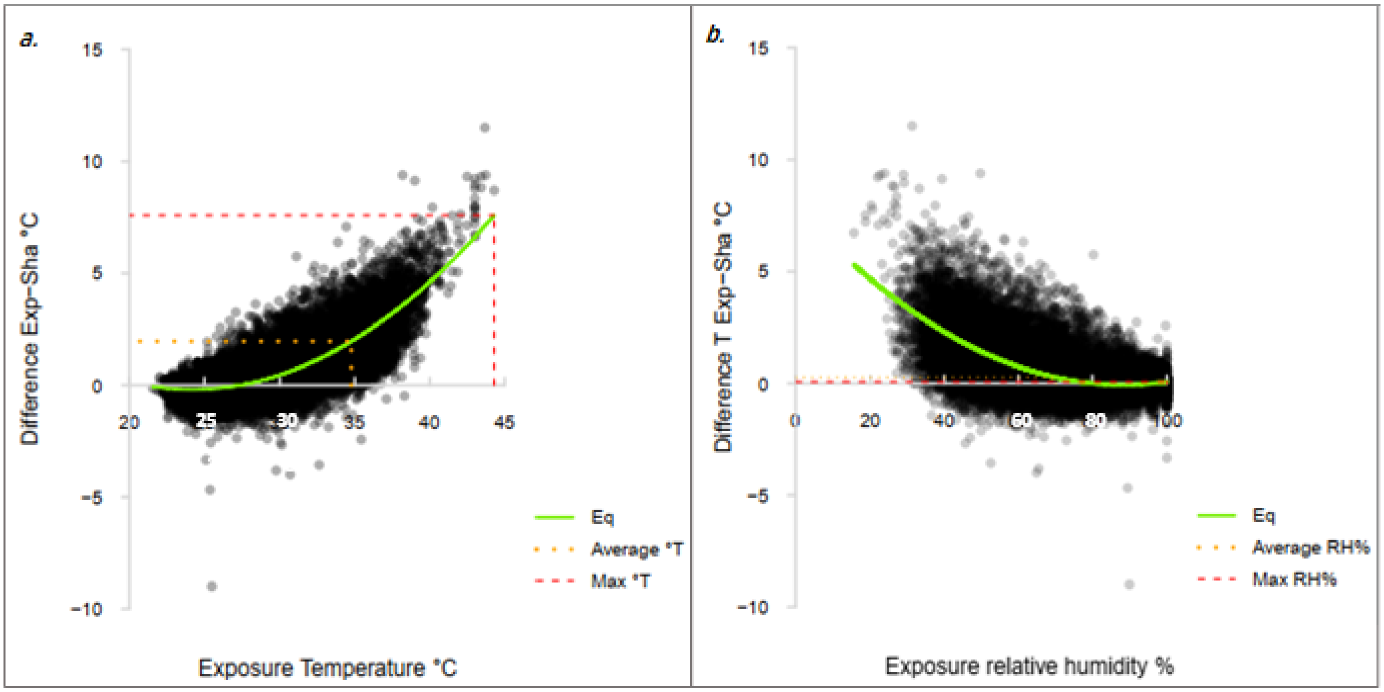

Figure 6 Effect of the air temperature and relative humidity of unshaded sensors on the temperature regulation (measured through the difference of temperature between unshaded and shaded sensors pair). Eq: equation.

Table 7 Parameters of the equations for temperature regulation due to trees based on air temperature and relative humidity of unshaded sensors.

Predictor: β	Parameter	Estimate	Standard error	p-value	Confidence interval 2.5 % / 97.5 %	AIC
Air temperature	*a*	0,019	0,0003	<2e-16 ***	0,019 / 0,02	63.221,49
	b	-0,931	0,0183	<2e-16 ***	-0,966 / -0,895	
	c	11,057	0,2743	<2e-16 ***	10,520/ 11,595	
Relative humidity	*a*	0,001	1,942e-05	<2e-16 ***	0,00098 / 0,0010	76.326,6
	b	-0,179	2,685e-03	<2e-16 ***	-0,184 / -0,174	
	c	7,840	8,826e-02	<2e-16 ***	7,667 / 8,013	

Equation 4: $T_{diff} = a \cdot \beta_{exp}^2 + b \cdot \beta_{exp} + c$. *a* and *b* slopes, *c* intercept. Determination coefficient (R^2), Akaike criterion (AIC), significance of predictors indicated by ($p < 0.1$), * ($p < 0.05$), ** ($p < 0.01$), *** ($p < 0.001$).

Based on Mora et al. (2017) lethal heat risk threshold, we found that in sensors under sun exposure, close to 82% of the days between December 2020 and May 2021 could be considered lethal heat events (i.e. with a significant extra-mortality due to increased hot conditions). However, this percentage diminished in sensors under tree shade to 63% of lethal days (Figure 7).

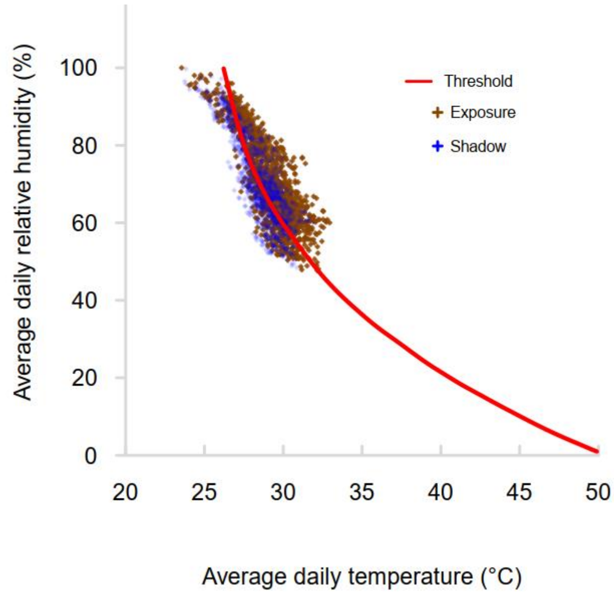

Figure 7 Average daily temperature and relative humidity for sensors unshaded (brown, n=1324 measurements) and under tree's shade (blue, n=1107).

Red line represents the support vector machine deadly threshold proposed by Mora et al. (2017)

Discomfort index

The number of daily records when the thermal discomfort was felt by the majority of people (DI >27) was around three times higher in sensors under sun exposure than in sensors under tree shade (33,8% versus 10,3% respectively). Most of these days occurred in March and April 2021 for those sensors exposed to the sun, especially in environments where there were fewer trees around; while in sensors under tree shade, the highest values of DI (greater than 27) were more common in April and May 2021 with the onset of the rainy season. During the beginning of the dry season, December 2020 and January 2021, the most severe and uncomfortable days were less frequent than in the rest of the time, with 14,5% of the days (65) in sensors without shade and 3,6% (4) on shaded sensors.

During the daytime, the hours that resulted uncomfortable for at least 50% of people in exterior sites (under sun exposure or not) started at 9:00 a.m. and lasted until 4:00 p.m. (Figure 8). However, there was a difference in the frequency of uncomfortable hours depending on the shade condition of the sensor as surrounding vegetation. Between 9:00 a.m. and 4:00 p.m., the number of records that had a DI value where the weather is considered strong and dangerous for people (DI> 29) was 4,5% of the records (400 of 8.824) in the shaded sensors, while that in the unshaded sensors there were 40,2% of the records (4.249 of 10.573), i.e. a multiplication by a factor 10. When sensors without shade were compared with each other, there was a higher frequency of high DIs (> 29) in sensors with fewer trees compared to those with a higher presence of trees. For instance, during the daytime in the studied period there was an increase up to 30% at 1:00 p.m. in records of unbearable weather in covers with fewer trees compared with periurban and grass covers. The records with values above the state of medical emergency (DI> 32) were only found in unshaded sensors between noon and until 3:00 p.m. but in a negligible amount, only 0,1% of the hourly records, which means 11 records during the daytime (9:00 a.m. until 4:00 p.m.) in the period studied.

Figure 8 shows how in sensors under tree shade, the records of high DI values decreased even in critical hours (9:00 a.m. - 4:00 p.m.) and there were no values higher than 32 (state of medical emergency) . However, the absence of DI values lower than 21, or comfortable, was noticeable in both types of shaded and unshaded sensors. The covers that meant better thermal comfort were those with dense trees and periurban and grass. The most comfortable hours were between 12 a.m. and 7 a.m., either on shaded or unshaded sensors on any cover.

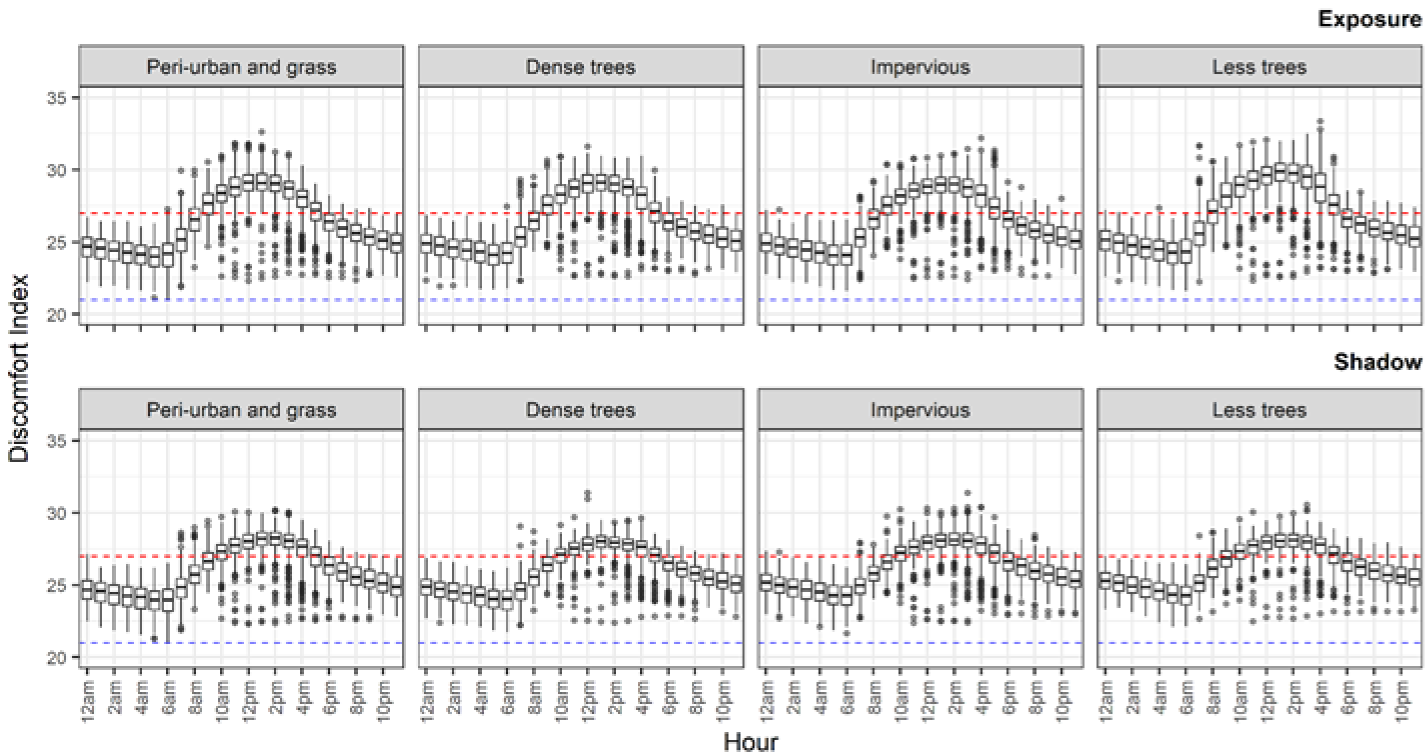

Figure 8 Average hourly (from December 2020 until May 2021) discomfort index for unshaded (exposure) and under tree's shade sensors. Red dotted line represents a limit (> 27) in which most the population suffers discomfort and blue dotted line means the limit (21) amidst no discomfort and uncomfortable environment.

Thermal comfort survey

Our survey sample consisted of 140 respondents who were equally distributed between gender. The mean age was 37 years and almost half of them had high school as the highest level of education (Table 8). Most of the respondents were from Puerto Carreño (49) and some tropical settlements (few cities) in the Orinoquia (Los Llanos in Venezuela) and Amazonia of Colombia and Venezuela (63), there were also people from other tropical cities in Colombia (17) and a smaller number of respondents (9) from cities with cooler climates in the two countries mentioned. Nearly all of the respondents (121) had been living in Puerto Carreño for more than 1 year, meaning they were acclimated to the weather since they were residents of the study area or were originally from similar climates. When asked why they were outdoors at the moment of the survey, the answers were mainly because the respondents were passing through (53%), for pleasure (26%) and because they worked on the street (20%, as informal vendors and cleaning services).

Table 8 Participant's characteristics across Puerto Carreño

Parameter	Total (%)
Gender	
Female	72 (51%)
Male	68 (49%)
Age category	
< 18	5 (4%)
18 - 23	19 (14%)
24 - 30	32 (23%)
31 - 45	47 (34%)
46 - 60	27 (19%)
> 60	10 (7%)
Highest level of school education	
Bachelor's degree	21 (15%)
Technician	37 (26%)
High school	64 (46%)
Elementary	12 (9%)
None	6 (4%)

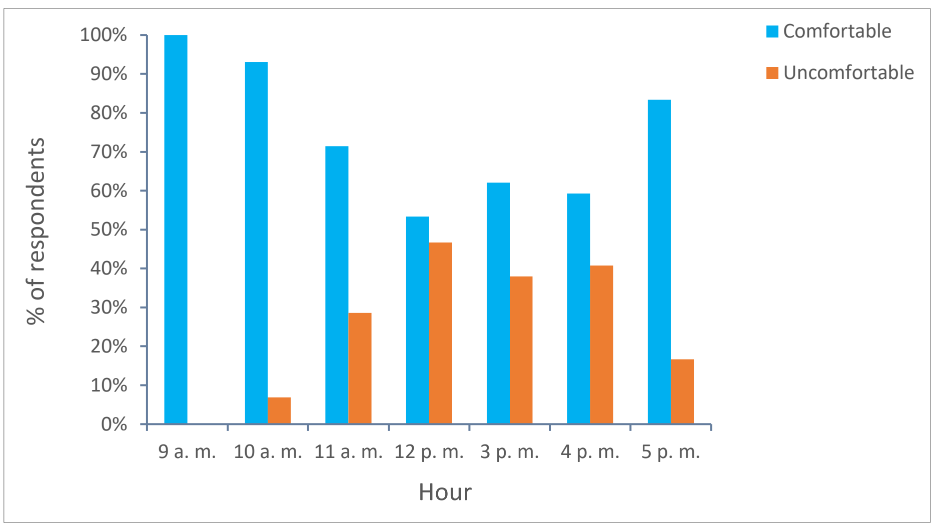

Figure 9 Percentage of respondents per hour in each comfort categories

During survey implementation, the most common responses were that the weather at that time was considered pleasant, but there was an increase in non-comfort immediately before and after noon (Figure 9). The comfort condition of the respondents with the climate at the time of the survey was confirmed by the degree of personal acceptability and tolerance demonstrated by most of them. Specifically, 111 people (79,3%) responded that the climate was acceptable, similarly, 114 (81,4%) people expressed that the climate was tolerable.

We identified no difference in the thermal comfort expressed by the respondents according to their gender, age, education level, shaded conditions and wind perception during survey implementation (Chi-square test, $p < 0,05$). On the other hand, there were significative differences in responses regarding thermal comfort due to solar radiation (chi-square = 39,9; p = 0,001499) and humidity (chi-square = 51; p = 0,0004998), as perceived by the participants during survey implementation. Correspondence analysis for both humidity and solar radiation shows that thermal comfort variance was explained using these variables for more than 93% (sum of the dimensions 1 and 2 in plots of Figure 10) as well as how high levels of thermal distress were linked with extreme conditions. Humidity levels that were more related with a thermal discomfort were humid and very humid, while a normal condition of humidity was more associated with comfort. As solar radiation was perceived as weak or normal, the respondents said that the climate was more comfortable (right panel Figure 10). Both, humidity and solar radiation correspondence analysis, confirmed that extreme weather (very and extremely uncomfortable) and strong conditions of these variables were related.

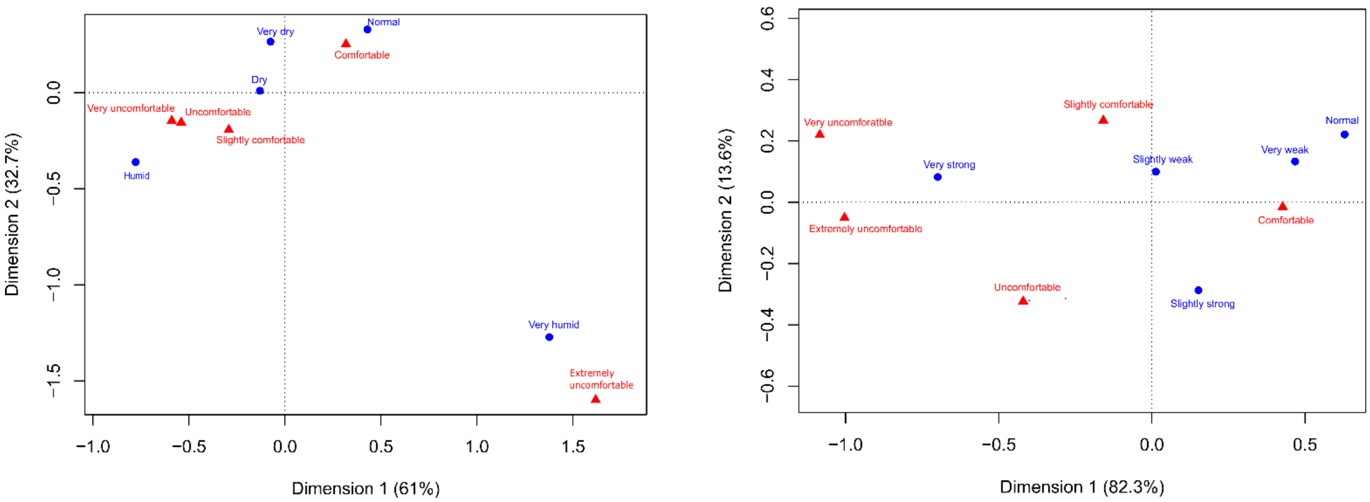

Figure 10 Correspondence analysis for humidity (left) and solar radiation (right) related with the thermal comfort expressed by respondents.

When asked about their awareness of trees, all the respondents recognized different benefits with the most common answers being the shade and cooling effect they give (131 people from 140, 93%). Also, some people (36, 26%) mentioned trees are a source of food, referring mainly to the mango tree and other fruits. Although many respondents recognized trees have many benefits just 11 people mentioned trees give them an overall sensation of "well-being". Regarding the respondent's proximity to the trees, 108 (77%) respondents expressed they had trees close to their houses and 32 people did not have, from this group of people just 6 (4%) said they would not have trees close to their houses. 92 (66%) respondents did not think trees lead to damage and harm in the city, however, the rest of the respondents (48) acknowledged the threats trees have especially during seasons with strong winds and rainy seasons due to their deficient management (for instance lack of pruning).

4 Discussion

This study analyzed the potential of urban forests in providing regulating ecosystem services in Puerto Carreño, a small Neotropical city in Colombia. Then using an integrated, mixed methods approach we estimated biomass-C stocks, the potential to regulate temperatures and human opinions on the effects of trees on well-being during the hot season in

2021. Due to the lack of information in Neotropical cities, this study also provides a sampling and measurement approach to better understand both biomass supply and temperature regulation, key carbon and climate regulating processes, by trees in tropical cities. Below we first describe and discuss our findings relative to biomass supplies and carbon. We then discuss findings on the temperature and humidity regulating effects. Third we then discuss how this measured thermal regulating process influence human well-being in terms of thermal comfort effects and citizen reported opinions on these benefits.

We found that Puerto Carreño's urban forest has a complex vertical structure consisting of large mature trees and palms, medium-sized trees and shrubs that grow along the streets, parks and patios of houses. We identified at least 70 different species, a value like that found for Valledupar in 200 random plots in parks and streets, 73 species, (Alcaldía de Valledupar, 2017), another lowland city in Colombia six times bigger than Puerto Carreño. Regarding the surface covered by trees, Puerto Carreño has a higher value than the reported for Medellín and Cali, the second and third most populated cities in Colombia, with percentages of 18%, 8,3% and 11,8%, respectively (Reynolds et al., 2017; Shiraishi, 2022), which represents a great difference in terms of surface cover by trees per inhabitant, 78 m^2/habitant versus 3,27 and 1,9 m^2/habitant correspondingly.

The average biomass per tree in Puerto Carreño is bigger (in a range of 337 and 461 kgC/tree) than the highest value reported for Bogotá (303 kgC/tree, Escobedo et al., 2015), this could be a result of mature trees of some species like *Mangifera indica*, *Samanea saman* and *Hymenaea courbaril,* common crown-spread species in lowlands of the tropics (Acuña-Simbaqueva et al., 2021; Alcaldía de Valledupar, 2017). Regarding the mean aboveground carbon stored per hectare, values reported for Puerto Carreño (between 37 – 51 tC/ha) were lower than those reported in Colombia for tropical humid forests (129,4 tC/ha; Galindo et al., 2011) and the forests of the Orinoquia region (81 tC/ha ± 23; Phillips et al., 2011), but bigger than those found for the urban forest in Bogotá (32 – 25 tC/ha; Dobbs et al., 2018) and Villavicencio (33 tC/ha, (Cortes & Matias, 2013).

Although Puerto Carreño is small in area when compared to other mega and medium cities in Latin America such as Rio de Janeiro, Santiago, Bogotá and Cali, there is a similarity in the lack of homogeneous distribution of trees in the urban area. Thus, while in the aforementioned cities the high-income areas are more diverse and better represented in terms of the number of trees and availability of green spaces (Escobedo et al., 2015; Shiraishi, 2022) compared with the low-income ones, in Puerto Carreño there are fewer trees in new neighborhoods nearby to the hilly rock outcrop areas (in the north and southeast sides close to the Meta and Orinoco rivers respectively) that are inhabited by indigenous people and migrants (Alcaldia Municipal de Puerto Carreño, 2016). At the same time, these areas lack basic needs such as potable water, energy and food, a situation very common in Vichada and the Orinoquia region (Distefano et al., 2022; Rozo et al., 2021).

The analysis of the temperature regulation by trees during the hottest season of 2021, December 2020 and May 2021, showed how the vegetative cover mitigates the heat effect in the city generating microclimate conditions (Gillner et al., 2015). However, this effect of the temperature regulation by trees was variable depending on the weather situation (hot days, cool and cloudy days, rainy days) and tree cover surrounding the sensor as reported by Mallen et al. (2020). The biggest differences for both temperature and humidity were found in the hottest months, February and March when fewer trees were present in both unshaded and shaded sensors (*Scattered trees*). Indeed, the presence of even a few trees helped to mitigate the temperature up to 7 °C during the hottest periods from 12:00 p.m. until 3:00 p.m., while keeping a higher humidity when compared to areas with sun exposure. On the other hand, during cloudy days (more common in April and May), temperature and relative humidity tended to be homogeneous even if the environment had few or many trees (Figures 4 and 5), proving the effect of thermal regulation is more important during heatwave events.

Vegetation cover and groups of trees have been documented to have an effect on the temperature regulation in cities (Coronel et al., 2015; Di Leo et al., 2016; Grilo et al., 2020; Rubiano Calderón, 2019; Wang et al., 2020) The greater the amount of vegetation (grass plus trees, backyards, vacant, parks), the cooler area will be (Bowler et al., 2010; Ossola et al., 2020) in general due to an increase in the evapotranspiration plus the effect of shade (Cavan et al., 2014). Our results confirm this, as the lowest temperatures (21,5 °C) were collected on sensors with higher grass cover (periurban and grass) compared to dense tree cover, even under sun exposure. The opposite situation occurs during nighttime and in the hours of non-radiation (from 5:00 p.m. to 6:00 a.m.) when there is an exchange of stored heat towards the atmosphere allowing a temperature regulation at night. This is especially true when the cover has scattered trees when there is no possibility that a dense tree canopy retains heat at night, as depicted in Figures 4f and 4h (Bowler et al., 2010).

These findings suggest that thermal regulation is non-linear in relation to heat intensity: *at higher daily heat extremes, those tropical urban forests cooling effects are maximized*. This is a notable result compared to the current knowledge which generally assumes a linear relationship (De Frenne et al., 2019; Ossola et al., 2020Gohr et al., 2021). To some extent, this is supported by the fact that urban forest in Puerto Carreño and other tropical cities (Acuña-Simbaqueva et al., 2021; Alcaldía de Valledupar, 2017; Reynolds et al., 2017) is highly diverse in species, structure and growth habits benefiting the appearance of traits that help to mitigate the effect of temperature in different ways (Helletsgruber et al., 2020; Rahman et al., 2020; Vieira et al., 2018). In addition, different types of urban vegetation vary in their capacity to mitigate local temperatures, in that sense a forest with more strata has greater capacity to reduce the air temperature whereas shrubs and pasture less (Richards et al., 2020).

Few studies in humid tropical lowland cities particularly in Latin America, have studied the effect of urban trees on temperature (Meili et al., 2021). Thus, our results showed that thermal regulation provided by trees In Puerto Carreño is several-centigrade grades higher at extreme temperatures (at 38,9°C vs 34,6°C in an environment with scattered trees). Furthermore, extreme high discomfort days (DI >29) are considerably more mitigated (factor 10) than high discomfort days (DI >27, factor 3) in shaded conditions compared to unshaded conditions. These results are confirmed by the lower number of days during the dry season that could become lethal in shaded conditions (63%) compared to those without shade (82%) based on the global threshold proposed by Mora et al. (2017). This indicates that urban forests can decrease the potential lethality of hot days by 23% in similar tropical city. This highlights, even more, the need for this adaptation measure to climate change leading to higher comfort and reduction of extreme heat mortality, particularly in the context of future increasing hot conditions in Puerto Carreño. Even if emergency levels of the Discomfort Index are still relatively rare in unshaded conditions (DI>32, 0,1% of the hourly records between 9:00 a.m. and 4:00 p.m.), these could highly increase in the future with or without shade up to 20% during the hottest hours assuming an increase +4 C°, according to the high-emissions 'RCP8.5' global warming scenario (IPCC, 2021).

Our findings are particularly relevant for a context such as Puerto Carreño, where according to an average ensemble scenario (for 2071 – 2100) there is an increase in average temperature from 28°C to 31°C (IDEAM et al., 2015) and an increase in the number of dry days and the frequency of droughts (IPCC, 2021). During the dry season of 2021 the results obtained for daily temperature and humidity are comparable to those found by Mora et al., (2017) and Guo et al., (2018) under the worst climate change scenario (RCP8.5) at the end of the 21st century. This shows that there is an increase in the heatwave-related excess mortality and in the number of days per year with climatic conditions that can become deadly (Figure 7), implying new hospital emergencies to which the city is currently unprepared. This means that Puerto Carreño in a quarter of the 21st century is close to what would be a global catastrophic climatic scenario at the end of the mentioned century.

Our study also linked the above measured climate regulating effects or urban forests to people's cognitive opinions and perceptions regarding these regulating effects on their well-being. Under the current weather conditions, people in Puerto Carreño are well adapted according to the information collected in the thermal comfort survey (Figure 9). We found that for a high percentage of respondents (more than 79%), the weather was tolerable and acceptable, and reported high levels of acclimatization (in terms of perceptions and clothing worn) to high temperature and relative humidity, independent of gender, education or age. Makaremi et al. (2012) and Villadiego & Velay-Dabat (2014), also found that local residents expressed more satisfaction with weather conditions in their places of residence when compared to visiting foreigners; in our sample most of the pedestrians (89%) were from the region or were born in warm weather places.

Overall, temperature was not perceived as an unpleasant factor as much as the solar radiation, contrary to the findings in Lai et al.'s (2020) global analysis. In general, respondents expressing discomfort with the weather, also recognized the sun as the most unbearable factor and it was more associated with a high thermal sensation, even though when asked during conditions with no direct solar radiation. Similarly, pedestrians highlighted the importance of trees as a mechanism for mitigating solar radiation and temperature (shade and freshness) as the most important value of the urban forest in Puerto Carreño. Although on humid days (before and after a rain event) respondents expressed a sensation of sultriness, the humidity was not identified as an important factor for their comfort and either they did not express a preference for drier weather.

5 Conclusions

This study focused on the potential of the urban forest in a small city in Colombia to function as a carbon stock and its capacity to regulate the temperature. Results revealed that Puerto Carreño has a mature urban forest with high complexity in terms of spatial and vertical structure and diversity despite the city's size; indicating it is an important carbon stock comparable with other bigger cities in the country. The carbon storage capacity (37 - 51 tC/ha) of the urban forest in Puerto Carreño is favored by the existence of big trees of species like mango, mamoncillo, or carob tree that not only provide shade, freshness, and aesthetics to the city but assure the food security of the most vulnerable populations, indigenous and displaced. Nevertheless, this capacity for storing carbon could be harmed by the lack of management and natural disasters caused by strong winds, as has occurred in the past. Accordingly, information and extension are needed to educate inhabitants on implementing adequate pruning practices to better sustain their existence. These findings on carbon stores and biomass supply now provide the municipality with information on how existing urban forests provide services to and improve the well-being of citizens.

Results also provide insights into the thermal regulation service provided by trees and showed how, even in a small city, this service is vital to mitigate the effects of climate change. With the current weather conditions during the driest season, this study documents that trees are indeed playing a role in protecting people against solar radiation and high temperatures, with differences up to 7 °C in extreme temperatures and 2 °C in normal conditions. Although people in the study area are adapted to the climate, they recognize the benefits of trees related to the temperature regulation and the existence of microclimates under the tree's shade, which will be more relevant in a future scenario of a higher incidence of climate change. This is one of the first studies addressing these issues in the Neotropics, the results presented here offer useful information about the mitigation and adaptation effect trees can have in the cities to fight climate change, not only at a national level but also at a regional level where it is expected to have notable impacts with increases in temperature.

Additional measures of the thermal regulation like the discomfort index and the thermal comfort survey, were applied and results that show that the ambient climate is still acceptable for respondents and most of the time comfortable. However, it was evident that future predicted extremely high temperatures that are not adequate for the human health, highlight the importance of developing indices that more adequate account for severe tropical contexts and providing more relevant information on people's comfort sensations, preferences, and physiological thresholds.

Some aspects can be studied for future research, for example, temperatures could be monitored through remote sensing that measures land surface temperature, and this real-time information could be used to implement preventive measures during heat event. Another area is understanding the effect of extreme tropical temperatures on the incidence of illness from an epidemiological point of view due to the current scenario during the hottest season. Accordingly, Nature-based Solutions and strategies could be used to mitigate impacts through the study of plant traits that help to regulate temperature. Additionally, understanding the role of the urban forest in Puerto Carreño in mitigating extreme events during the rainy season and its contribution in the reduction of the flood risk is important. This study is one of the first to attempt to provide such information in these small tropical cities that are home to an increasing number of the world's vulnerable populations.

Specific contributions of the student

Diana Lucia did the literature review and designed the sampling to measure the biomass and the thermal regulation, besides she took all the data in the field during December 2020, January and February 2021. All the data collected by sensors were sent by a local collaborator each 15 days. Diana Lucia analyzed all the data for both biomass and climate, from which she wrote the results, discussion and conclusions of this document.

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Appendix 1

Table A1. Common indices used to determine thermal comfort. Adapted from Chow et al. (2016), Cheung and Jim (2018), Guzmán (2018)

Category	Indices	Description
Direct	Humidex	Combine air temperature (T_a) and air vapor pressure (e) to give a scale[+] of the temperature that is perceived. $Humidex = T_a + 0{,}5555 * (e - 10) \quad [°C]$ [+]20-29 °C No discomfort; 30 – 39 °C some discomfort; 40 - 45 °C high discomfort; > 46°C dangerous.
	The wet-bulb globe temperature (WBGT)	It is the weighing between the meteorological wet-bulb temperature (T_{wb}), air temperature (T_a) and globe temperature (T_g). $WBGT = 0{,}7 * T_{wb} + 0{,}2 * T_g + 0{,}1 * T_a \quad [°C]$ Thresholds: moderate (high) at 26 (28) °C; 32 °C excessive
	Temperature humidity discomfort index (THI)	Combine air temperature (T_a) with relative humidity (RH) $THI = (0{,}8 * T_a) + \left(\frac{T_a * RH}{500}\right)$ THI uncomfortable range in the tropics is >30.1 ◦C – based on research in equatorial Malaysia
Rational	Physiological equivalent temperature (PET)*	Based on the balance between two human nodes (core and skin). PET is the reached air temperature under hypothetical conditions without the wind and radiation (indoor conditions), in which the heat balance of the human body is maintained with node temperatures equal to the outdoor conditions being assessed. The environmental conditions for indoor spaces are RH equal to 50% at 20 °C. The comfort range is between 26 – 30 °C
	Modified Physiological equivalent temperature (mPET)*	Based on PET but including some varitions of RH, water vapor and clothing. mPET uses a multi-segment model of the human body and a multilayer model for clothing. The comfort range is between 26 – 30 °C
	Universal thermal climate index (UTCI)*	Based on the Fiala multi-node model of human thermal balance, for reference variables (*Ta=MRT*[+], *wind speed*=0,5 m/s at 10 m of heigth, and *e* associated with a RH=50%). For high temperatures *e* = 20Hpa. [+] Mean Radiant Temperature UTCI assumes the physiological characteristics of a person who is walking at 4 km/h in outdoors with a metabolic rate of heat production of 135 W/m. Besides UCTI includes an adaptative clothing model determined by real conditions. Its range of application is restricted to -50 and 50 °C, and wind speeds between 0,5 and 17 m/s.

*To get the indices of PET, mPET and UTCI, the RayMan model (Modelling of Mean Radiant Temperature and Thermal Indices) is a recognized tool that allows the calculation and display of the number of hours with solar radiation, the sky view factor (SVF), shade calculation and global radiation estimation (Guzmán, 2018). The model Bioklima is also used to calculate UTCI (Cheung and Jim, 2018).

Appendix 2 Treatment of atypical data from the CJEG sensor (unshade):

The following protocol is based on testing several correction equations such as: linear, power, exponential. We found the Multivariate Imputation by Chained Equation offered a trade-off between simplicity and satisfactory fit. Accordingly. the next steps correspond to this method:

1st step: Sensor data was split into two datasets *before* and *after* bird nest was established (March 16th 2021).

2nd step: With the dataset *after* the nest, data with a difference of temperature between sun exposure and shade bigger than 3 °C (the maximum difference achieved before the nest was 3,168 °C) was filtered.

3rd step: The dataset *before* was split by hours, then using a Multivariate Imputation by Chained Equation (MICE) algorithm (van Buuren, 2018), a set of five equations for each hour were fit using the temperature under trees as a predictor for that location (Equation 3). Then to obtain a single equation for each hour, the five equations were combined using the pool function of the MICE package from the R language 4.1.0 (van Buuren & Groothuis-Oudshoorn, 2011).

$$T_{exp} = a + b \cdot T_{sha} \qquad (3)$$

Where:

T_{exp} = Temperature of the sensor under sun exposure

T_{sha} = Temperature of the sensor under tree cover

a = intercept

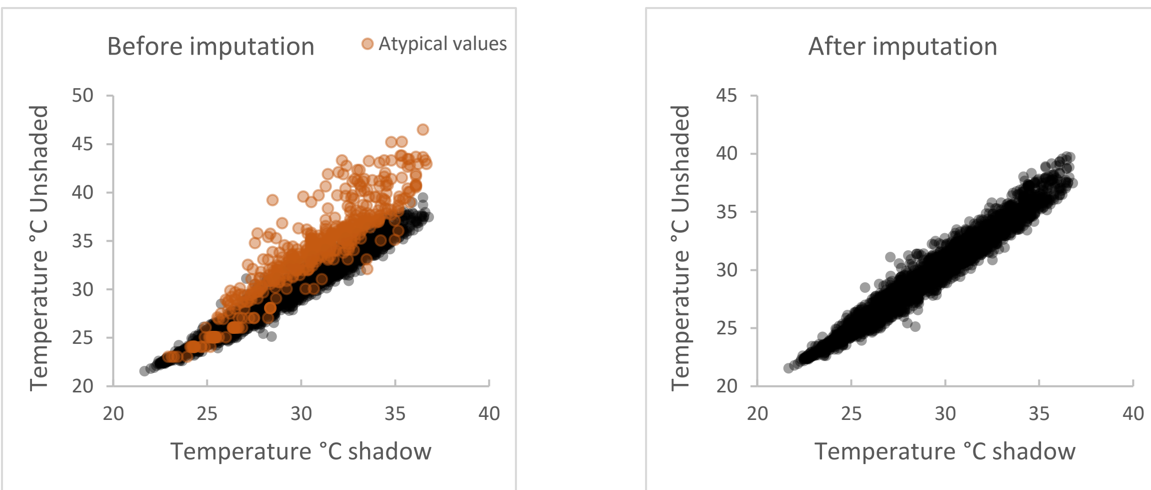
b = slope

4th step: With the equations for each hour the atypical data detected in the 2nd step were recalculated. Equations employed for each hour are presented in Table A2, also the plots before and after the imputation are presented in Figure A1.

Table A2. Parameters of equations for each hour

Hour	a	b
12:00:00 a. m.	1,59	0,93
1:00:00 a. m.	0,39	0,97
2:00:00 a. m.	7,95	0,67
3:00:00 a. m.	8,24	0,65
4:00:00 a. m.	8,36	0,64
5:00:00 a. m.	7,97	0,66
6:00:00 a. m.	3,89	0,83
7:00:00 a. m.	2,15	0,93

Hour	a	b
8:00:00 a. m.	5,91	0,82
9:00:00 a. m.	0,33	1,03
10:00:00 a. m.	6,41	0,83
11:00:00 a. m.	8,23	0,78
12:00:00 p. m.	7,37	0,81
1:00:00 p. m.	9,58	0,74
2:00:00 p. m.	11,77	0,68
3:00:00 p. m.	8,54	0,77
4:00:00 p. m.	3,04	0,93
5:00:00 p. m.	21,17	0,33
6:00:00 p. m.	20,32	0,32
7:00:00 p. m.	18,52	0,36
8:00:00 p. m.	16,93	0,40
9:00:00 p. m.	15,74	0,42
10:00:00 p. m.	2,35	0,90
11:00:00 p. m.	2,07	0,91



Supplementary Figure A1. Temperature CJEG Sensors Unshaded and shadow, before (left panel) and after (right panel) the imputation to treat atypical values

Appendix 3 Survey questionnaire

ID____ **Date:**_________ **Land use:** Residential ( ) Commercial ( ) GZ/Park ( ) **Radiation:** Unshaded ( ) Tree shade ( ) Shelter ( ) **Time:** _______ **Age**: ____ **Gender** F ( ) M ( ) **Education level**: None ( ) Pre-scholar ( ) Elementary ( ) High school ( ) Professional ( ) Technician ( ) Other: ________ **Occupation:**____________ **Origin** _____________ **Department** __________ **Neighborhood** ____________ **Time living in:** Years ( ) Months ( ) Days ( ) **Position:** Sitting ( ) Standing ( ) **Dressing:**____ **Reason for being outside** Passing through ( ) Pleasure ( )

1. Thermal perception

1.1. How are you feeling now?

-2 Cool
-1 Slightly cool
0 Neutral
1 Slightly warm
2 Warm
3 Hot
4 Very hot

2. Thermal comfort (affective evaluation)

2.1. You think this environment is:

0 Comfortable
1 Slightly comfortable
2 Uncomfortable
3 Very uncomfortable
4 Extremely uncomfortable

3. Thermal preference

3.1. Please say how you would prefer to be now:

-3 Much cooler
-2 Cooler
-1 Slightly cooler
0 Neither hot nor fresh
+1 A little warmer
+2 Hotter

4. Personal acceptability

4.1. On a personal level this environment is for you:

0 Acceptable rather than unacceptable
-1 Unacceptable more than acceptable

5. Personal tolerance

5.1. This weather is:

0 Perfectly tolerable
1 Slightly difficult to accept
2 Quite difficult to accept
3 Very difficult to accept
4 Intolerable

6. Humidity sensation

-2 Very dry
-1 Dry
0 Ok
1 Wet
+2 Very humid

7. Wind sensation

-2 Immobile
-1 Little wind
0 Ok
1 Windy
+2 Very windy

8. Sensation of solar radiation

-2 Very weak
-1 Slightly weak
0 Ok
1 Slightly strong
+2 Very strong

9. What is the least pleasant factor?

( ) Temperature
( ) Humidity
( ) Wind
( ) Solar radiation

10. Do you have trees near your house?

( ) YES ( ) NO

11. If not, do you want to have it?

( ) YES ( ) NO Why ______________________________________
____
____

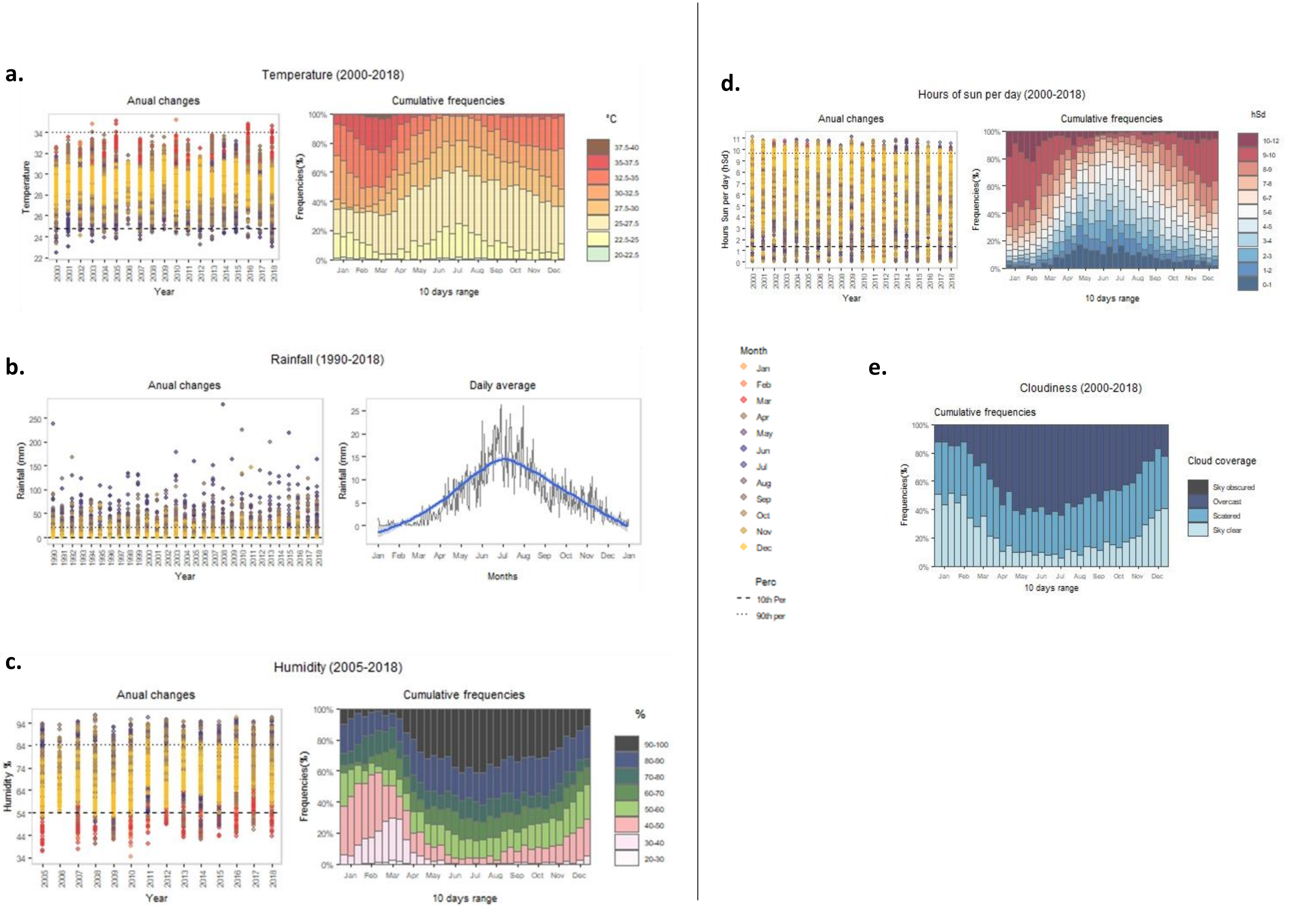
12. Have you experienced excessive heat at night?

( ) YES ( ) NO

13. What are the benefits (services) and damages (disservices) of trees in the city?

____
____
____
____

Appendix 4. Supplementary Figure A2. Meteorological characteristics and context for the city of Puerto Carreño, Colombia.



Appendix 5. Results of the accuracy assessment of the non-supervised classification of the tree cover

Table A3. Confusion matrix

	Non Tree	Tree	TOTAL	Accuracy
Non Tree	252	8	**260**	0,96923077
Tree	14	60	**74**	0,81081081
TOTAL	**266**	**68**	**334**	
Accuracy	0,94736842	0,88235294		
Overall accuracy				93,413174%
Kappa parameter				80,334011%