Geoderma 417 (2022) 115840

Contents lists available at ScienceDirect

Geoderma

journal homepage: www.elsevier.com/locate/geoderma

Urban soil management in the strategies for adaptation to climate change of cities in the Tropical Andes

Santiago Bonilla-Bedoya [a,b,e,*], Miguel Ángel Herrera [b], Angélica Vaca [c], Laura Salazar [d,e], Rasa Zalakeviciute [f], Danilo Mejía [g], Magdalena López-Ulloa [h]

[a] Research Center for the Territory and Sustainable Habitat, Universidad Tecnológica Indoamérica, Machala y Sabanilla 170301, Quito, Ecuador
[b] Department of Forest Engineering. E.T.S.I.A.M., Campus de Excelencia Internacional Agroalimentario (ceiA3), Universidad de Córdoba, Córdoba, Spain
[c] Institución de Investigación Geológico y Energético, Quito Ecuador
[d] Centro de Investigación de la Biodiversidad y Cambio Climático (BioCamb), Universidad Tecnológica Indoamérica, Quito, Ecuador
[e] Ingeniería en Biodiversidad y Recursos Genéticos. Facultad de Ciencias del Medio Ambiente. Universidad Tecnológica Indoamérica, Machala y Sabanilla, 170301 Quito, Ecuador
[f] Intelligent & Interactive Systems Lab (SI2 Lab) and Biodiversidad, Medio Ambiente y Salud (BIOMAS), Facultad de Ingenierí ay Ciencias Agropecuarias (FICA), Universidad de Las Américas, 170125 Quito, Ecuador e Centro de Estudios Ambientales, Universidad de Cuenca, Ecuador
[g] Centro de Estudios Ambientales, Universidad de Cuenca, Ecuador
[h] Ingeniería en Agroecología, Universidad Regional Amazónica Ikiam, Tena Ecuador

ARTICLE INFO

Handling Editor: Budiman Minasny

Keywords:
Climate change
Volcano cities
Urban soils
Soil organic carbon
Adaptation strategies

ABSTRACT

The unique characteristics of a city amplify the impacts of climate change; therefore, urban planning in the 21st century is challenged to apply mitigation and adaptation strategies that ensure the collective well-being. Despite advances in monitoring urban environmental change, research on the application of adaptation-oriented criteria remains a challenge in urban planning in the Global South. This study proposes to include urban land management as a criterion and timely strategy for climate change adaptation in the cities of the Tropical Andes. Here, we estimate the distribution of the soil organic carbon stock (OCS) of the city of Quito (2,815 m.a.s.l.; population 2,011,388; 197.09 km^2) in the following three methodological moments: i) field/laboratory: city-wide sampling design established to collect 300 soil samples (0–15 cm) and obtain data on organic carbon (OC) concentrations in addition to 30 samples for bulk density (BD); ii) predictors: geographic, spectral and anthropogenic dimensions established from 17 co-variables; and iii) spatial modeling: simple multiple regression (SMRM) and random forest (RFM) models of organic carbon concentrations and density as well as OCS stock estimation. We found that the spatial modeling techniques were complementary; however, SMRM showed a relatively higher fit both (OC: $r^2 = 20\%$, BD: $r^2 = 16\%$) when compared to RFM (OC: $r^2 = 8\%$ and BD: $r^2 = 5\%$). Thus, soil carbon stock (0–0.15 m) was estimated with a spatial variation that fluctuated between 9.89 and 21.48 kg/m^2; whereas, RFM showed fluctuations between 10.38 and 17.67 kg/m^2. We found that spatial predictors (topography, relative humidity, precipitation, temperature) and anthropogenic predictors (population density, roads, vehicle traffic, land cover) positively influence the model, while spatial predictors have little influence and show multicollinearity with relative humidity. Our research suggests that urban land management in the 21st century provides key information for adaptation and mitigation strategies aimed at coping with global and local climate variations in the cities of the Tropical Andes.

1. Introduction

Anthropogenic activity is the most important driver of landscape transformation (Butzer, 1964; Ellis, 2015; Ellis et al., 2013; Goldewijk et al., 2017; Kaplan et al., 2011). Human disturbance affects surface reservoirs and exacerbates potential changes in the global climate system (Eglinton et al., 2021; Friedlingstein et al., 2018). In this sense, landscapes with a predominantly urban matrix show alterations in their

* Corresponding author.
E-mail addresses: santiagobonillab@hotmail.es (S. Bonilla-Bedoya), mherrera@uco.es (M. Ángel Herrera), laurasalazar@uti.edu.ec (L. Salazar), danilo.mejia@ucuenca.edu.ec (D. Mejía).

https://doi.org/10.1016/j.geoderma.2022.115840
Received 29 November 2021; Received in revised form 14 March 2022; Accepted 17 March 2022
Available online 22 March 2022

biogeochemical cycles that potentially affect regional and global atmospheric climates (Lorenz & Lal, 2009).

On the other hand, the carbon residing in vegetation and soils is three times that of atmospheric carbon (Eglinton et al., 2021) and is a key player in mitigating or increasing the accumulation of greenhouse gases. However, the terrestrial carbon cycle constitutes one of the major uncertainties affecting global change modeling (Carvalhais et al., 2014).

By 2018, the global urban land area increased at a rate of change of 1.5 times compared to 1990, reaching a total coverage of approximately 797,076 km2 (Gong et al., 2020). This increase happens mainly in the US and China, but countries such as India, Russia, Brazil, France, among others, show sustained increases in urbanization (Seto et al., 2012; Liu et al., 2018; Gong et al., 2020).

These regions engendered a carbon footprint five times larger when compared to developing regions (Müeller et al., 2013), such as tropical areas. Urban expansion in the tropics would contribute about 5% of atmospheric emissions due to deforestation and land use change (Baccini et al., 2012; Bonilla-Bedoya et al., 2020). This scenario intensifies the conversion of the global biogeochemical cycle which latently affects climate and surface carbon pools (Butzer, 1964; Lorenz & Lal, 2009; Kaplan et al., 2011; Ellis, 2015; Ellis et al., 2013; Goldewijk et al., 2017; Friedlingstein et al., 2018; Eglinton et al., 2021).

Therefore, the skyrocketing global increase of impervious surface (Chen et al., 2021; Liu et al., 2018) requires an accurate spatial analysis of the world's built-up areas; thus, having recent spatio-temporal databases for studying the world's built-up areas expansion (Klein Goldewijk et al., 2010; Liu et al., 2018; Potere et al., 2009; Schneider et al., 2010; Seto et al., 2018; Gong et al., 2020) will contribute to the improvement of spatio-temporal modeling of local and global carbon dynamics in an urban world.

In regions such as Latin America and specifically in the cities of Tropical Andes countries (TACs), urbanization and its associated impacts potentially began in the pre-Columbian period with the transition from country to city driven by an agricultural technological revolution. The European conquest of the region put an end to the evolution of Amerindian urbanism, and urban centers were used by the state as a means of political consolidation and social and economic control. Thus, in the 19th century, independence, characterized by a warlike environment, left the urban territories divided into smaller nation-states. In the second half of the 19th century and the beginning of the 20th century, the reconstruction of the state was consolidated, associated with the emergence of European industrial economies and the primary city, where goods for export were collected and processed (Reid, 1986; Carrión, 2010).

The presence of regional urban centers supported by rural production and the industrialization of the 20th century continued to drive rural–urban migration and the trend toward the intensification of the city (Reid, 1986) and its peripheries and metropolization. During the second half of the 20th century, introspection became more prominent along with a shift to consider the built city in a framework of globalization (Carrión, 2010). Now, in the first two decades of the 21st century, urban sprawl, hyper-urbanization, and the development of intermediate cities are some of the elements that characterize the urbanization dynamics in the region (Bonilla-Bedoya et al., 2020; Inostrosa et al., 2013).

Research has shown that the cities of TACs and their mountain ecosystems are at greater risk of global warming impacts than cities in other regions and ecosystems (FAO, 2015; Herzog et al., 2011). The neotropical highlands (1000–3500 m.a.s.l.) maintain a historical population concentration that is explained by climate and soil fertility. Cities such as Bogota (population 11.2 M, altitude 2640 m.a.s.l.), Quito (population 2011 M, altitude 2815 m.a.s.l.), and La Paz (population 0.766 M, altitude 3640 m.a.s.l.) are shaped by the landscapes of the inter-Andean valleys of volcanic origin. In this sense, the geographic scope of urban processes and the demographic trend in the region indicate that 80% of the population is or will be urban by 2050. This phenomenon, complemented with a scenario of change, is an urgent challenge for urban planning focused on sustainable development (Bai et al., 2016) and oriented to the welfare and environmental justice of the cities in the region (Bonilla-Bedoya et al., 2020). For example, for Quito, in the last 100 years, it was estimated that the average temperature increase fluctuated between 1.2 and 1.4 °C (Zambrano-Barragán et al., 2011).

Quantifying the effects of urban environments on the physical, chemical, and biological properties of soil from a spatio-temporal perspective is complex because urban soils have high spatial and temporal variability (Bonilla-Bedoya et al., 2013), which is dependent on the parent material, the urban land use, and other factors. Thus, it is difficult to define a soil or a community of soils in space–time (Canedoli et al., 2019; Morel et al., 2015; Pouyat et al., 2002; Pouyat et al., 2015). However, contemporary urban planning will need to understand the relationship between the soil organic carbon stock and the different biophysical and anthropic dimensions of an urban socio-ecological system in order to maintain or optimize its functions, services, and benefits and avoid its loss or degradation through informed management decisions, citizen participation, and the application of technology (Rawlins et al., 2013).

Therefore, the aim of this research was to determine the spatial distribution of soil OCS in a city in the inter-Andean valley and to analyze the potential relationships between this distribution and the different dimensions of an urban socio-ecological system in a dynamic of change. Such information will be critical for the development of nature-based strategies (Hobbies & Grimm, 2020) and policies that aim to improve the climate adaptation and resilience capabilities of urban environments experiencing environmental variations.

For this purpose, the following objectives were set. First was the collection of urban soil samples considering a spatial design that allows the reduction of spatial variability and the establishment of a baseline for temporal analysis. Second was the estimation of the organic carbon pool in the soil through the application of geostatistical and geoinformatics models based on linear and machine learning methods that estimate the spatial distribution of organic carbon contents and estimate soil bulk density via variables relevant to the socio-ecological system. From a spatial perspective, the three types of predictors were (i) the geographic proximity and spatial relationship between samples, (ii) spectral predictors from the SPOT 7 sensor, and (iii) spatial predictors of urban planning contained in a series of cartographies developed for this research. The third objective was to discuss the effects of biophysical and anthropic predictors on model formulation.

2. Materials and methods

2.1. Quito

Urban Quito expands along an inter-mountain valley (197.09 km^2) over a deposit of volcanic material elongated in the north–south direction and narrow in the east–west direction (Fig. 1). This city, located in the Tropical Andes (2,815 m.a.s.l.), is inhabited by ~ 1.874 million people. However, its population is projected to increase to ~ 2.353 million people by 2035 (Bonilla-Bedoya et al., 2019; UN, 2015, 2019).

The predominant soil orders in the Quito valley are Andisols, Molisols, and Entisols with Andean characteristics. Its soils, of volcanic origin, are formed by two dominant pedogenesis dynamics. The first is directly related to the properties of the volcanic expulsion material and the weathering of its vitreous particles. A second dynamic is related to the accumulation of OC in the soil organic matter (OM). This process depends on environmental conditions and weathering, which vary with altitude and latitude, as well as on the parent materials on which these soils were formed (Shoji et al., 2015). Furthermore, the formation of the urban soil of the Andean valleys it is associated with the accretion of sediments from the foothills of the Andean mountains range as well as anthropogenic disturbance through urban land use (Forman, 2014).

However, in the last 100 years, the city has recorded an increase of

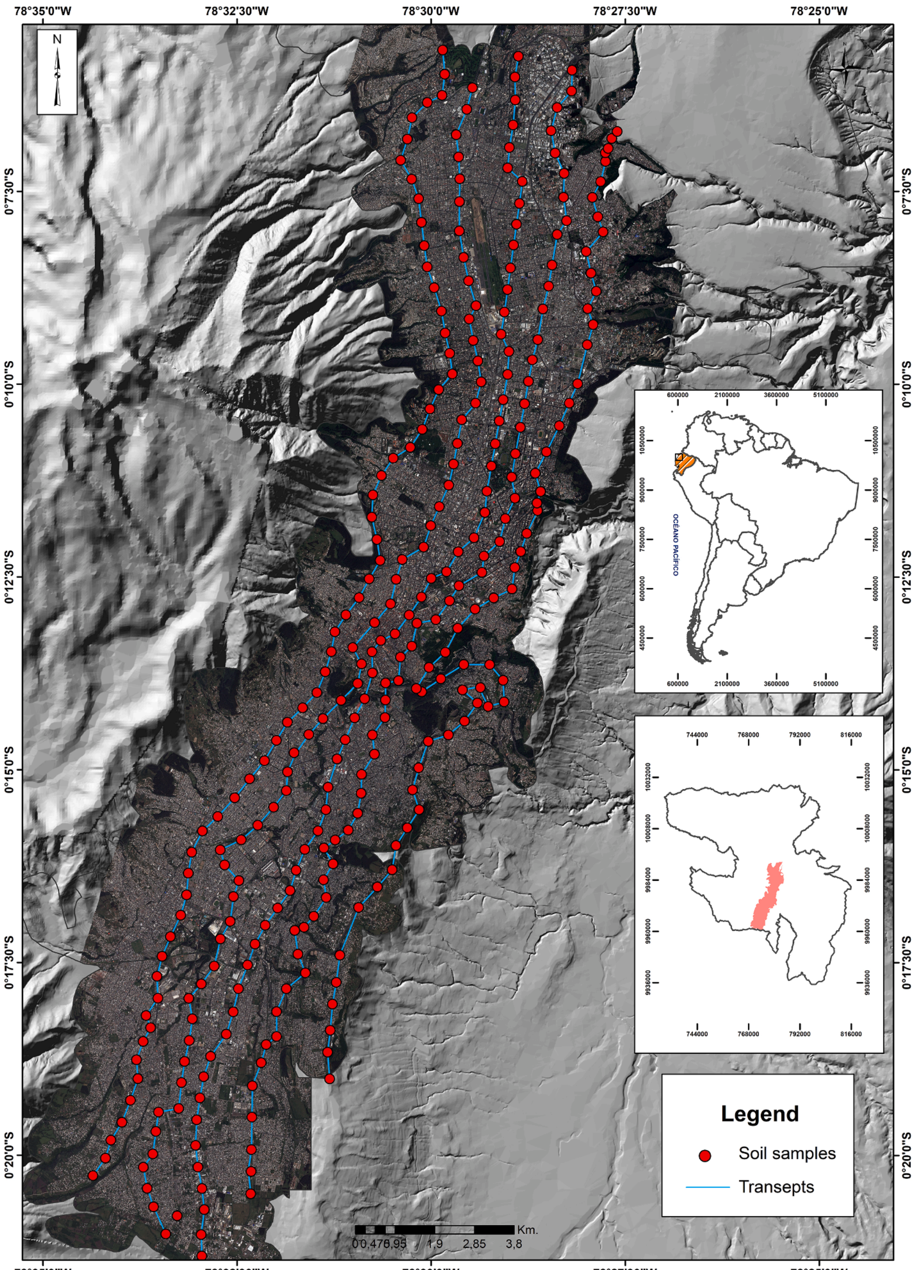

Fig. 1. Quito Valley and topography. Blue lines: transects located on the main road axes that transversally cross the urban area of the city. Red dots: locations of soil sample surveys; depth 0–15 cm. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

1.2 to 1.4 °C in its average temperature (13.14 °C) (Zambrano-Barragán et al., 2011). It also reports increases in monthly minimum (1.5 °C) and maximum (29.9 °C) temperatures, both in magnitude and frequency, and in the intensity of extreme precipitation (Vicenti et al., 2016; Zambrano-Barragán et al., 2011).

Like other cities with inclusive governance, for example: New York, London, and Durban (Anguelovski & Carmin, 2011), Quito has been promoting programs that address climate change and protect environmental quality (Carmin et al., 2012b). However, as commonly observed in cities in low-income countries, Quito's challenges are rooted in the development of infrastructure for waste treatment, affordable housing, and transportation (Carmin et al., 2012).

2.2. Soil sampling and soil organic carbon stock quantification

To determine the spatial distribution of soil OCS in an inter-Andean valley city and to analyze the possible relationships between this distribution and the different dimensions of a socio-ecological system we established five transects (30.5 ± 0.54 km in length/each) that considered the five road axes that transversely cross the entire urban area of the city. In each transect, 60 survey points were generated using the Create Random Points tool of ArcGIS 10.8.2. Thus, we surveyed a total of 300 samples composed of four subsamples taken at each point at a depth of 0–15 cm and at ~ 500 m intervals. The survey points considered exposed soils along sidewalks, streets, and parks; generally, soils on which urban vegetation is supported. None of the samples were under concrete cover (Fig. 1).

To estimate BD, per transect, we took five equally distributed samples along each transect, for a total of 30 samples, using cylinders (250 cm^3). The data obtained from these samples were used to construct a logistic regression (r^2 = 0.33) that was used to cover the remaining BD data.

The quantification of OM was done by loss on ignition, following the method proposed by Schulte and Hopkins (1996). Twenty grams of each soil sample were dried in an oven for 24 h at 105 °C. Then, the samples were cooled in a desiccator to subsequently weigh ∼ 5 g ± 0.5 g. This sample was added to porcelain capsules and allowed to ash for 3 h at 450 °C. The porcelain capsules were then removed and transferred to the desiccator, and, after cooling, the weight was again recorded. The calculation of OM was performed by weight difference at the different temperatures according to:

$$\% \text{ OM} = (\text{weight } 105\ ^\circ\text{C} - \text{weight } 360\ ^\circ\text{C})/\text{weight } 105\ ^\circ\text{C})*100). \quad (1)$$

The organic carbon (OC) value was obtained by dividing the % OM by the Van Bemmelen factor (1.724).

$$\%\text{OC} = \%\text{OM}/1.724. \quad (2)$$

To estimate BD, using cylinders (250 cm^3), we took five undisturbed soil samples at a distance of ∼ 6 km from each transect. These 30 samples and the OC contents of these points were used to construct a logistic function ($r^2 = 0.33$) that related OC concentrations to BD (g cm^3).

$$\text{OCS kg/m}^2 = \text{OC}\%/100{*}\text{BD kg/m}^3{*}0.15 \text{ m} \quad (3)$$

2.3. Data analysis and modeling

To estimate the soil OCS (kg/m^2) in a depth interval of 0–0.15 m, we applied linear and machine learning models: simple multiple regression models (SMRM) and random forest models (RFM), thus modeling the spatial distribution of OC (%) and BD (kg/m^3); the percentage of coarse soil fragments (Nelson and Sommers, 1996; Poeplau et al., 2017; Rovira et al., 2007) was discarded since no coarse fragments were observed in our samples. The models used predictors of i) geographic proximity, ii) spectral co-variables (SPOT 7), and iii) urban planning spatial co-variables (Table 1).

2.3.1. Geo-statistics model

We fit an SMRM, which considers a possible linear nature of urban growth (Allen & Lu, 2003; Landis & Zhang, 1998; Bonilla-Bedoya et al., 2020), to quantify its effects on the soil OCS in city soils. For modeling, we used the Rstat package (Fox et al., 2017). Previously, we checked the assumptions of multicollinearity, heteroscedasticity, and normality. For sample size, we applied a Kolmogorov Smirnoff test to each variable (Birnbaum & Tingey, 1951; Marsaglia & Wang 2003). When the distribution was not normal, we applied different ways of fitting, including the bcPower/yjPower functions of the Car R package (Yeo & Johnson, 2000; Fox et al., 2015), until we obtained histograms close to the normal distribution. Finally, the model had a spatial representation; this procedure was executed through Spatial Analysis Tool extension of ArcGIS 10.8.2.

2.3.2. Geoinformatics model

The RFM is a machine learning technique recognized as a tool for spatio-temporal predictions (Prasad et al., 2006; Cutler and Cutler, 2012; Boulesteix et al., 2012; Hengl et al., 2015; Vaysse & Lagacherie, 2015; Olson et al., 2018; Bonilla-Bedoya et al., 2021; Nussbaum et al., 2018; Hengl et al., 2018). It has been shown to be optimal and with comparable results to models based on geostatistical techniques (Hengl et al., 2018a; Hengl et al., 2018b; Hengl & MacMillan, 2019). Thus, using the predictors (Table 1), we fit an RFM model (Hengl et al., 2018a; Hengl et al., 2018b; Hengl & MacMillan, 2019) in R Project. To obtain the best model, the algorithm (Hengl & MacMillan, 2019) was run several times using different hyper-parameters (García, 2018).

The accuracy of the model was estimated from the out-of-bag (OOB) error data. This information was useful to establish the number of trees in the model, which considered the relationship between the number of trees and the OOB error rate (Patri & Patnaik, 2015; Quan & Valdez, 2018), a relationship necessary to identify the number of trees that is efficient in terms of storage (Abat, 2020).

The number of variables (mtry) that the algorithm selects is by default, a partition between the total number of variables divided by three. However, we applied several tests with different mtry to identify the best results of the model. Finally, to analyze the effect of the variables in the model, we used variable importance by random permutation of the variables (Breiman, 2001; Parr et al., 2018).

Table 1
Predictors, co-variables, ranges, and references of data used to run models of organic carbon and bulk density.

Predictors	Co-variables	Range	Reference
Spatial predictors	DEM	2641–3439	PLEIADES images
	Slope	0–77.63	PLEIADES images
	Temperature	12.26–14.49	Monitoring Stations Quito Secretary of Environment
	Precipitation	706.77–1459.88	Monitoring Stations Quito Secretary of Environment
	Relative humidity	69.35–73.11	Monitoring Stations Quito Secretary of Environment
	$PM_{2.5}$	16.35–21.52	Monitoring Stations Quito Secretary of Environment
Spectral predictors	Red	625 – 695 nm	Spot images
	Green	530 – 590 nm	Spot images
	Blue	455 – 525 nm	Spot images
	NIR	760–890 nm	Spot images
	NDVI		Spot images
Antrophic predictors	Population density	0.09–822.29	National Institute of Statistics and Census
	Land cover classification	a. Agriculture Forests Green areas Impervious Shrub and herb Soil Water	Object-based image analysis classification Spot images
	Green Infraestructure	a. Green sidewalks (<50 m2)Sports fields (50–999 m2)Neighborhood parks (1000–9999 m2)Medium parks (10000–99999 m2)Large park (100000–999999 m2) Metropolitan parks (>1000000 m2)	Object-based image analysis classification Spot images
	Distance to sample	10-20…500	Multiple ring buffer
	Distance to roads	10-20…500	Multiple ring buffer
	Vehicular traffic	1–10	Traffic intensity

3. Results

The spatial distributions of the soil OCS concentrations and bulk density were obtained from geo-statistical and geo-computational models (Figs. 2, 4, 5). The application of SMRM (Table 2) was effective in understanding the relationships between the socio-ecosystem and urban soil carbon stock. The estimated goodness-of-fit magnitude of the model explained $r^2 = 20\%$ (standard error: 0.09) and $r^2 = 16\%$ (standard error: 0.09) of the variation of OC and BD, respectively. This model yielded spatial concentrations in a range of 0.05–16.24% of OC. In the case of bulk density, the spatial ranges were between 0.88 and 1.51 g cm^3 (Fig. 2).

Regarding RFM, the r^2 (OOB) of the models explained 8% and 5% of the variation of OC and BD, with a low error rate (Figs. 4 and 5) for both OC (0.0008) and BD (0.0090), respectively. RFM also presented the lower, middle, and upper ranges of OC concentrations in the city: 3.43–4.89%, 6.17–10.55%, and 9.13–17.45%, respectively (Fig. 4 a, b, c). The lower, middle, and upper ranges of BD were 0.918–1.008 g cm^3, 1.099–1.161 g cm^3, and 1.226–1.286 g cm^3, respectively (5 a, b, c). The models were fitted by testing different hyper-parameters. An mtry calibration of 5 for OC and 3 for BD were the models that gave the best results (Table 3). Similarly, the relationship between the number of trees and the OOB error rate showed that 300 trees for OC and 100 for BD yielded the lowest error rate. (Fig. 3).

Finally, the two preliminary results of each model were used to estimate the spatial distribution of COS in the tropical Andean city of Quito. Thus, considering the results from SMRM, we found that the OCS in the first 0.15 m of the soil presented a spatial variation that fluctuated between 9.89 and 21.48 kg m^2, while when considering the models adjusted from RFM, the spatial variation of the soil OCS fluctuated between 10.38 and 17.67 kg m^2 (Fig. 6).

Alternatively, the review of the assumptions prior to the model and the significance of the variables for its adjustment led us to consider the following 5 of the 17 variables used at the beginning: DEM, Slope, Relative humidity, Population density, and Distance to roads (Table 2).

Where the RFM was concerned, variable importance considered the 17 variables grouped into spatial, spectral, and anthropic predictors. For variables with poor predictive ability, random replication caused a slight increase in accuracy due to random noise. This resulted in small negative significance scores, which can be considered as equivalent or zero significance. Spatial and anthropogenic predictors showed greater importance in the fit of the OC and BD soil models. Among the spatial predictors were precipitation, temperature, relative humidity, PM $_{2.5}$, and DEM, while the anthropic predictors included roads, traffic, and distance to sample (Fig. 7).

4. Discussion

Our results contribute to develop some methodological design strategies that consider soil (Hobbie & Grimm, 2020) as a key component of adaptation measures towards global climate variation in tropical Andean cities. Thus, we provide spatial evidence of the potential eco-

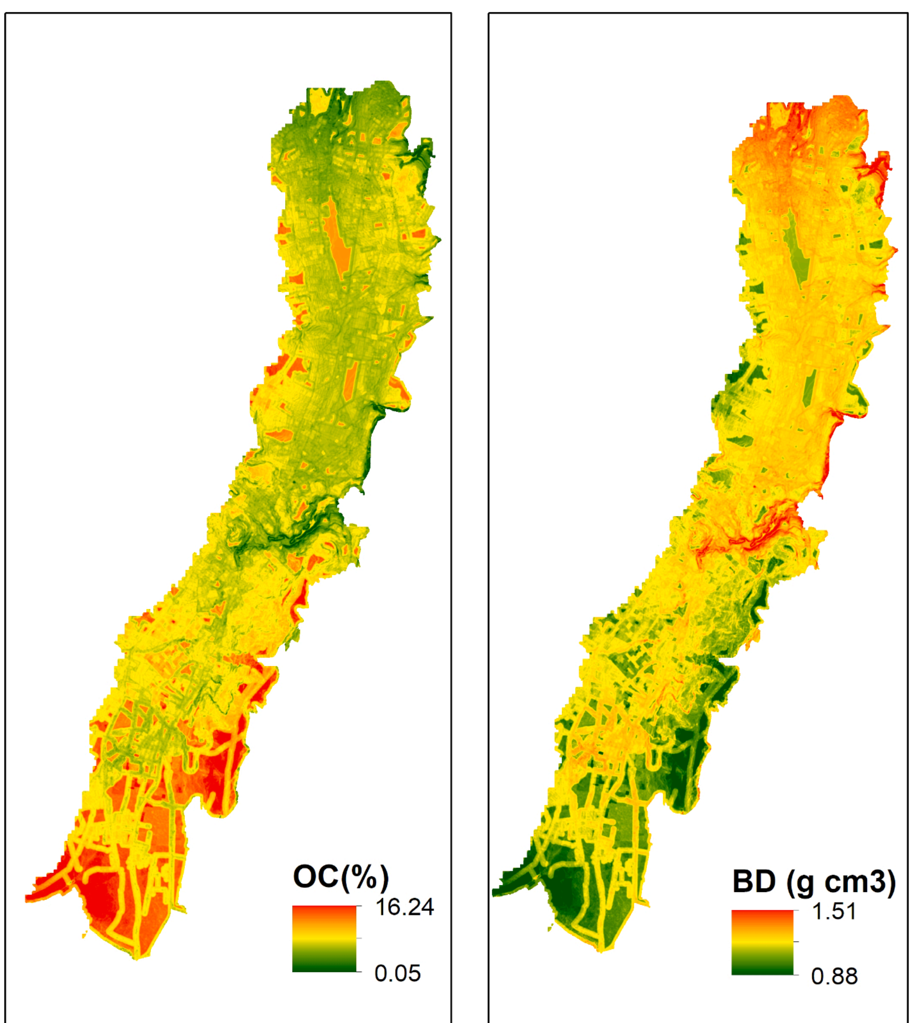

Fig. 2. Simple multiple regression and random forest models for organic carbon concentration and bulk density (g cm^3).

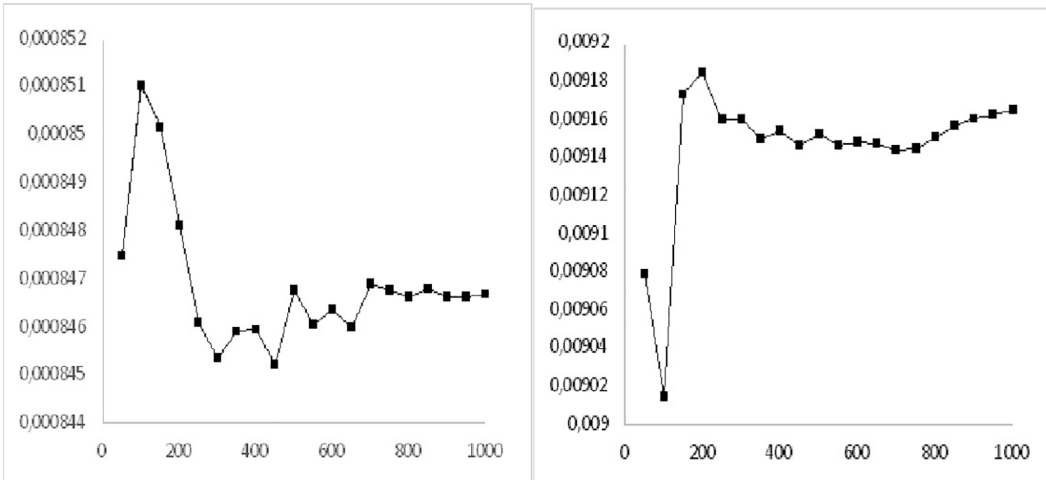

Fig. 3. Out-of-bag error data with respect to the number of trees for organic carbon and bulk density.

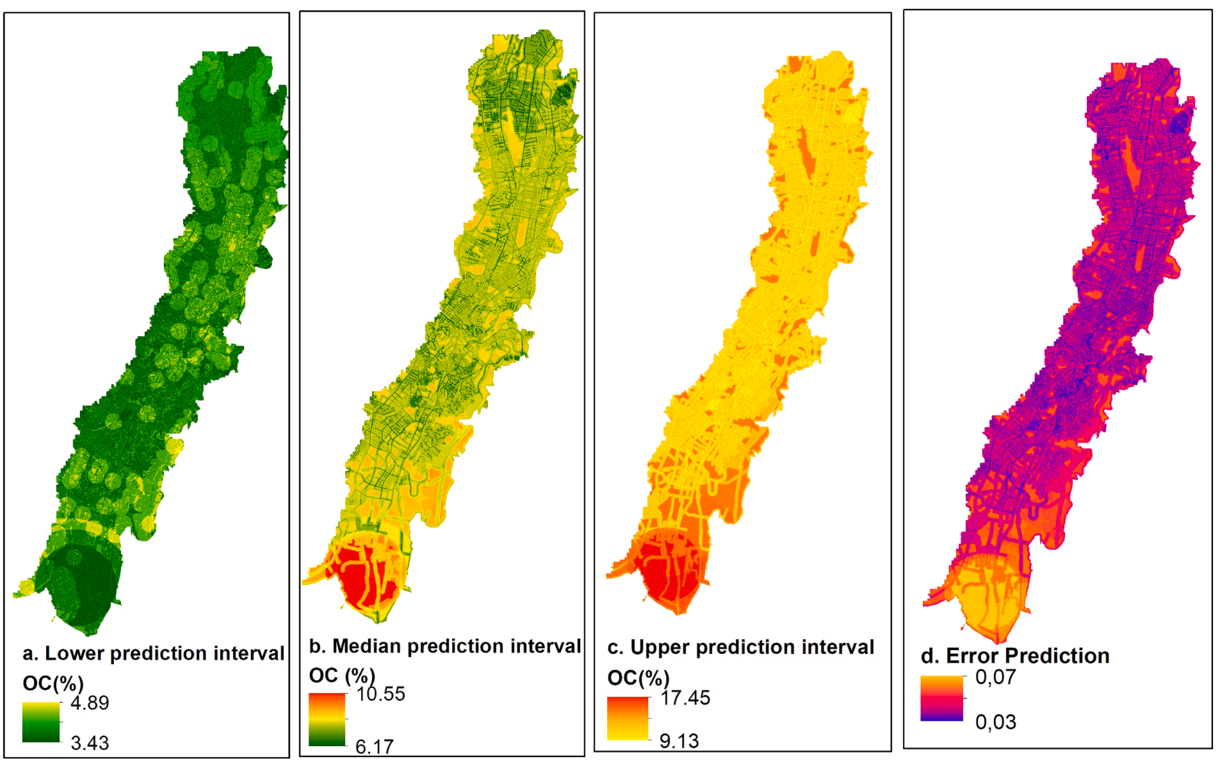

Fig. 4. Random forest spatial prediction model for organic carbon concentrations; a. lower prediction intervals, b. median prediction intervals, c. upper prediction intervals, and d. Error prediction.

systemic functions of urban soil (Bonilla-Bedoya, 2016). However, the estimates presented here should be monitored from a spatiotemporal approach, improving the sampling designs, the number of samples collected and the search for interactions between covariates to improve, in the medium term, the results analysis.

The two types of models fitted to our data are complementary; both SMRM and RFM provide timely information and show spatial congruence in expressing the spatial distribution of soil OCS in the urban landscape of the Quito valley. However, SMRM showed a relatively better fit. Comparing the performance of the two spatial models in others studies (Smith et al., 2013, Xi et al.; 2020; Bremm Pluth et al., 2021; Yuchi et al., 2018), we found that their results vary. In some cases, the best model fit is through SMRM (Smith et al., 2013); in other cases, RFM is reported as the best-performing technique (Xi et al.; 2021; Bremm Pluth et al., 2021); and similar results are also reported between the two models. These variations are attributed to the size and noise of each dataset and also to the linear/non-linear and hierarchical relationships between OC/DA and the predictors (Xi et al., 2021).

In regard to the significance of the co-variables, some of these were common to both models. SMRM showed how the OC storage potential in soils relates to the spatial predictors of altitude, relative humidity, and slope, aligning with other studies (Merriman et al., 2017) in demonstrating the effect of biophysical factors as special predictors that enhance the capacity of urban soils to store OC. In the case of RFM, this technique placed in order of importance the spatial predictors of temperature, precipitation, relative humidity, and altitude; the first

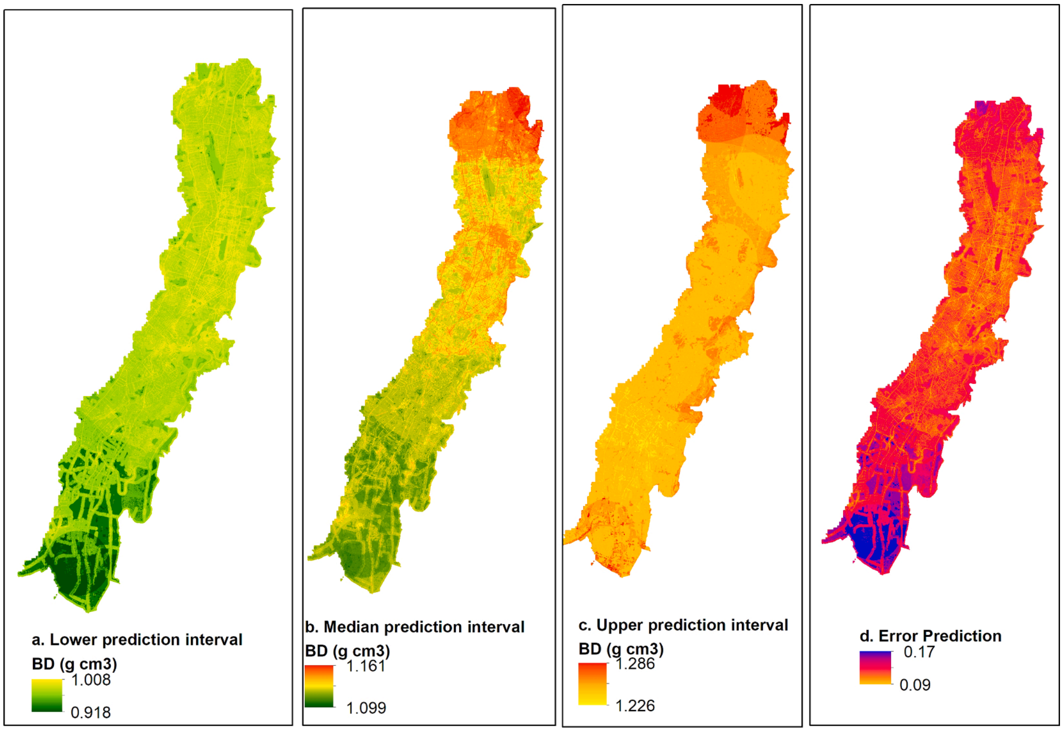

Fig. 5. Random forest spatial prediction model for bulk density; a. lower prediction intervals, b. median prediction intervals, and c. upper prediction intervals, and d. Error prediction.

Table 2
Simple multiple regression model: Estimate, standard error, and p-value (<0.01) of the covariates.

	OC			BD		
	Estimate	Std. Error	P-Value	Estimate	Std. Error	P-Value
(Intercept)	−0.0031	0.1014	0.9756	−0.0031	0.1014	0.9756
DEM	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Population density	0.0001	0.0000	0.0335	0.0000	0.0000	0.0335
Relative humidity	−0.0027	0.0016	0.0932	−0.0027	0.0016	0.0932
Slope	−0.0003	0.0001	0.0150	−0.0003	0.0001	0.0150
Distance to roads	0.0744	0.0164	0.0000	0.0745	0.0164	0.0000

variables (temperature and precipitation) were discarded in SMRM as were the spectral predictors due to their high multicollinearity with the co-variable of relative humidity, significant in all models.

Alternatively, the significant anthropic predictors in SMRM were population density and distance from roads, variables reported in other studies as determinant in the enrichment and anthropic contamination of urban soil (Bonilla-Bedoya et al., 2021). The anthropic predictors in RFM likewise evidenced the importance of these variables in addition to PM $_{2.5}$, vehicular traffic, and land cover as elements to consider in urban soil studies (Bonilla-Bedoya et al., 2020b).

As to spectral predictors, for RFM, spatial data (normalized difference vegetation index [NDVI]) and the blue band (455–525 nm) influenced the spatial distribution of organic carbon and bulk density, respectively. Pettorelli et al. (2005) discuss the importance of NDVI to understand the responses of vegetation and ecosystems and the increase in surface temperature of natural environments. Furthermore, in urban environments, correlations between NDVI and certain human conditions, such as welfare and segregation, have been reported (Bonilla-Bedoya et al., 2020a).

4.1. Biophysical predictors: Topography, relative humidity, precipitation, and temperature

This research evidences the effect of the altitudinal gradient and climate moderation on urban soils located in tropical mountainous systems (FAO, 2015; Njeru et al., 2017) and supports the notion that the organic carbon storage timeframe of tropical soils and vegetation is shorter than that of soils and vegetation at temperate and boreal latitudes (Carvalhais et al., 2014). Thus, it is reasonable to conclude that spatio-temporal variations in precipitation, temperature, and topography affect the evolution and spatial variation of different soil orders in mountain cities. For example, Njeru et al. (2017) reported a positive linear relationship ($r^2 = 0.30$) between altitude and OC content in an altitudinal gradient of the East African mountain systems (867–1441 m. a.s.l.). Therefore, future OC storage in tropical Andean urban soils will depend on the climate, which will potentially be characterized by increasing temperatures in the inter-Andean valleys and increasing precipitation on both Andean slopes (Carmona & Poveda, 2014; IPCC,

Table 3
Random forest model fitting for spatial prediction of organic carbon and bulk density.

Atributes	Number of trees	Sample size	Independent variables	Mtry:	Target node size:	Variable importance mode:	Splitrule:	OOB prediction error (MSE):	R squared (OOB):
Organic carbon	300	300	17	5	5	Permutation	Variance	0.0008	0.081
Bulk density	100	300	17	3	5	Permutation	Variance	0.0091	0.050

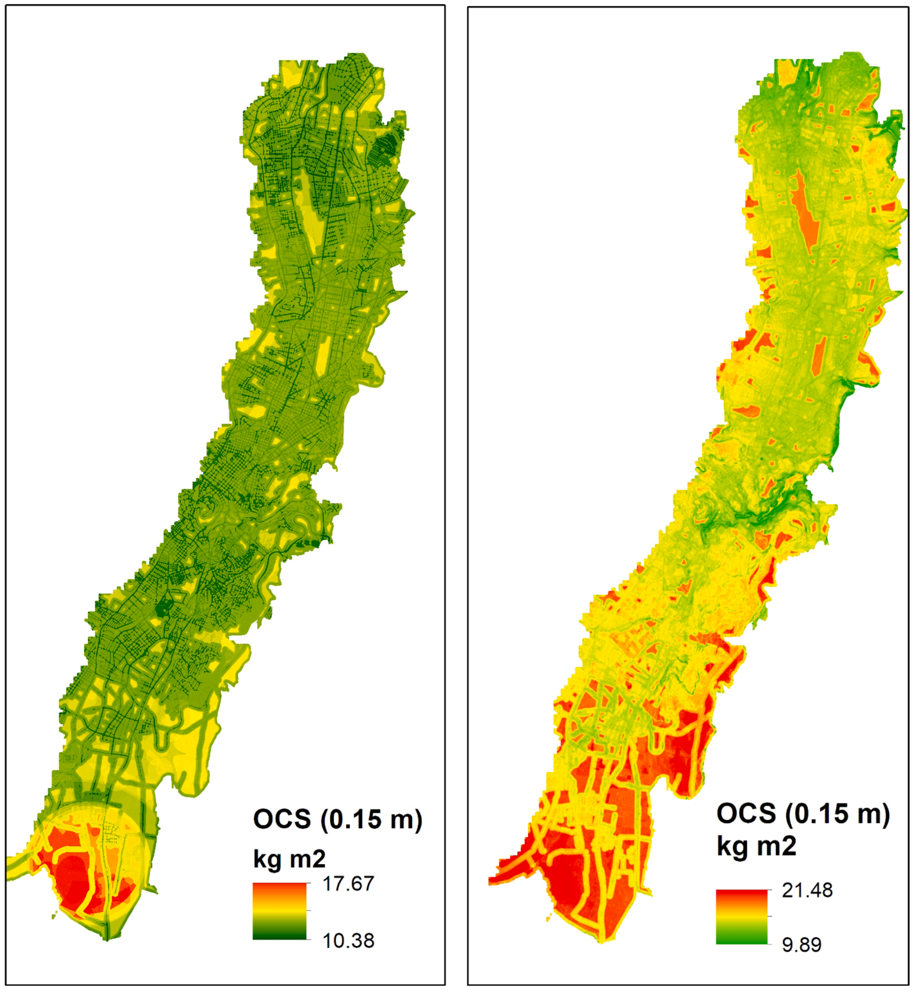

Fig. 6. Estimation of the spatial distribution of soils organic carbon stock using spatial distributions of organic carbon concentrations and bulk density in the inter-Andean valley of Quito. Left, Soil organic carbon stock derived from Random forest models; Right, Soil organic carbon stock derived from simple multiple regression models.

2014; Martínez et al., 2011; Pabón-Caicedo et al., 2020).

In the specific case of Quito, with its volcanic origin and urban gradient landscapes, it was found that the altitudinal, precipitation, and thermal characteristics of the Tropical Andes determine the pedogenesis of the andic soils or soils with andic characteristics (Shoji, 1994). We found that the soils had a high organic matter content and good physical properties. A high potential anionic or cationic exchange capacity would thus be expected, as reported by others (Galindo & Bingham, 1977; Huygens et al., 2005).

It is worth noting that although the impact of temperature and precipitation on soil organic matter decomposition is a widely discussed topic (Davidson et al., 2000; Giardina and Ryan, 2000), recent research has shown that some soil quality indicators (e.g., moisture and temperature) influence soil OCS gains and losses more than purely climatic variables (Kerr & Ochsner, 2020). Therefore, the incorporation of these variables in future distribution models could reduce uncertainty and improve the estimates presented in this research (Table 3).

In peri-urban forest ecosystems adjacent to the study area, Terán-Valdez et al. (2019) report a relatively stable variation in soil OC content for the different natural ecosystems. Our data reveal the existence of high spatial variability in the estimated carbon content for the urban area of Quito, with values between 10.38 and 17.67 ton kg m-2 in the upper 0.15 m of soil. Therefore, it is to be expected that this variation is also related to the soils pedogenesis and natural ecosystems prior to the settlement of the city, which are clearly differentiated: in the extreme south, by the predominance of Andisols and Molisols on which the last fragments of high montane evergreen forest of the city still settle; while, to the north, on Andisols and Entisols, relicts of semi-deciduous forest and scrublands of the northern valleys are established; on these a high vulnerability to the process of urban expansion is reported (Bonilla-Bedoya et al., 2020a).

This ecosystemic variation in the city is evidenced in the vegetation and soil. On one hand, ground surface temperatures are moderated through an island effect attributed to vegetation and its density, mainly urban trees and shrubs (Edmondson et al., 2016). On the other hand, soils with lower bulk density are associated with a higher organic carbon richness, resulting from the low density of organic materials combined with higher porosity (Al-Shammary et al., 2018). This scenario intensifies toward the south, in the foothills of the Atacaso volcano (Fig. 8), where the last fragments of high montane evergreen forests in the city have been observed (Bonilla-Bedoya et al., 2019). In contrast, the soils of the northern part of the city, with higher bulk density values and lower porosity, correspond to the semi-deciduous forest and shrubland of the northern valleys. Here, soils that are more vulnerable to compaction, with lower concentrations of OM, and less aggregation and less possibilities of root penetration are found (Al-Shammary et al., 2018; USDA-NRCS, 2019). Spatial models show the vulnerability of this ecosystem to urban expansion (Bonilla-Bedoya et al., 2020a). In this sense, soils in the south of the city would show greater resistance to water erosion and the dispersion of soil aggregates due to a high

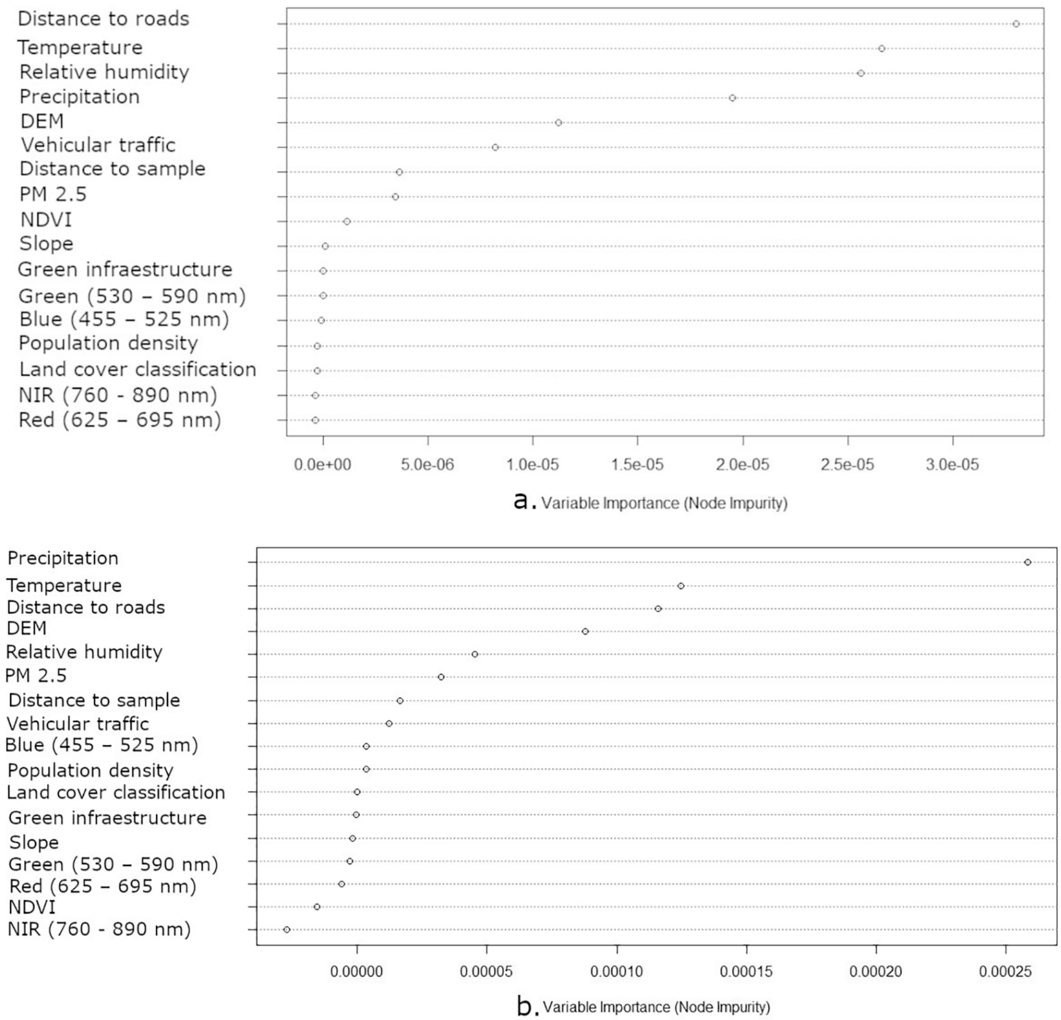

Fig. 7. Importance relationship of the co-variables for the modeling of: a) organic carbon and b) bulk density.

permeability, which reduces runoff when compared to soils in the north.

4.2. *Anthropic predictors: population density, road axes, vehicular traffic, $PM_{2.5}$, distance between samples, and land cover*

Regarding anthropogenic predictors, we can observe how the urban landscape and its interacting elements perturb the surface reservoirs, influence the global climate system (Eglinton et al., 2021; Friedlingstein et al., 2018), and affect the spatial distribution of COS.

Our results dispute the approach of Pouyat et al. (2015), who argued that urban soil management effects are greater than environmental effects. Like other studies in the area (Bonilla-Bedoya et al., 2021), our data demonstrate how spatial predictors are an important element in the modeling of landscape soil attributes and are complemented by the anthropic predictors proposed here.

However, we do agree with Pouyat et al. (2015) in regard to how the anthropic effect is more widespread and goes beyond the limits of most urban areas. However, we would like to add that the natural ecosystems surrounding the city are determinants in the resilience of the socio-ecosystem. Here, we demonstrate that the study and management of land in the spatial planning of an urban–rural-natural gradient could enhance the ecosystemic services derived from the soil structure and function. Similarly, we agree with Edmondson et al. (2012) and Canedoli et al. (2019), who suggested an underestimation of the potential contributions of urban land in mitigating extreme climate variation. Therefore, land cover, land use planning, and the intra-urban relationships of the fragments that compose the urban landscape would enhance the OC storage capacity of urban soils (Barkhordarian et al., 2018; Bonilla-Bedoya et al., 2021; Foley et al., 2005; Hart and Sailor, 2009).

The effect of intra-urban land cover on the urban thermal environment and its rural setting is widely known; for example, in Leicester, England, an increase of 0.6 °C was reported in a peri-hyper-urban gradient due to heat island effects (Edmondson et al., 2016; Hart and Sailor, 2009). Barkhordarian et al. (2018) attributed the increase in maximum and minimum temperatures (especially during the months of December, January, and February) over the northern Tropical Andes to anthropogenic activity.

Therefore, urban adaptation to climate change must consider the natural environments on which the city sits, promote their restoration, diversify the fragments that make up the urban landscape, and increase the interactions between fragments, such as the relationship between green and blue-gray cover (Hintz et al., 2017; Masson et al., 2020).

Impervious surfaces have been reported to drive local and possibly regional climatological effects due to their radiative, thermal, aerodynamic, and moisture properties (Edmondson et al., 2016). The effects include significant increases in air temperature in and around cities. This effect of anthropogenic activity on microclimates, known as the urban heat island, has been widely studied in temperate zones and more recently in tropical zones (Arnfield, 2003; Masson et al., 2020).

This reinforces the need for both governments and urban planners to effectively manage urban vegetation in 21st century cities (Bonilla-

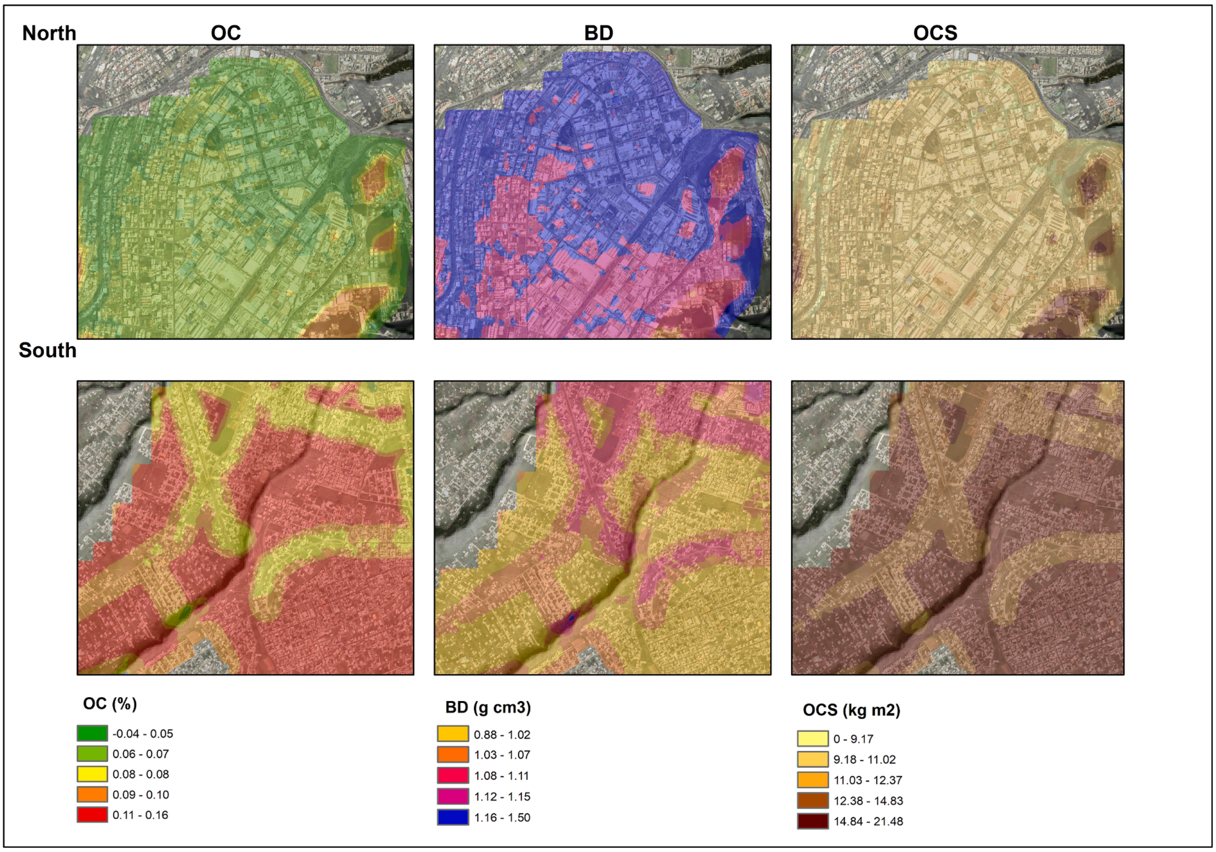

Fig. 8. Estimated spatial distribution in the extreme north (associated with semi-deciduous forest and shrub ecosystems) and south (High Montane Evergreen Forests) of Quito. SMRMs of organic carbon concentrations (%), bulk density (g cm^3), and soil organic carbon stock (kg/m^2).

Bedoya et al., 2020a,b; Calaza et al., 2018; Luederitz et al., 2015; Ordoñez-Barona et al., 2020). Green infrastructure acts as a hinge between the social and ecological subsystems; it is also an instrument for achieving other goals, such as environmental justice and equitable access to ecosystem benefits and services (Bonilla-Bedoya et al., 2020a,b). Its social (Bonilla-Bedoya et al., 2020a,b; Escobedo et al., 2015; Favaro et al., 2016; Gerrish and Watkins, 2018; Greenstein and Smolka, 2000; Jenerette et al., 2011), economic (McMahon & Benedict, 2000), and public health benefits (Bonilla-Bedoya et al., 2020a,b; McMahon & Benedict, 2000) continue to be reported for cities in the region and for mitigating climate variation (Edmondson et al., 2016).

However, we agree with Manuel-Navarrete et al. (2019) that evolutionary pressures acting on social groups would favor gray over green infrastructure due to competitive advantages in terms of the concentration capacity and intensive use of resources. Our study area is no different—recent changes in urban land cover demonstrate that permeable infrastructure continues to grow into spaces with potential for the establishment of green infrastructure (Bonilla-Bedoya et al., 2021). Overcoming this competition requires a strengthening of the collective intentions that aim to transition to a 21st century city (Manuel-Navarrete et al., 2019). It also requires evaluating adaptation measures that can improve the potential impacts related to land cover, including changes in infrastructure practices and in the development of green infrastructure under a contemporary planning approach (Bai et al., 2018; Rawlins et al., 2013).

5. Conclusions

The monitoring and management of urban soils is a criterion that is perfectly integrated in the development of sustainable cities and in the design of adaptation and mitigation strategies aimed at assessing/estimating climate variation that affects the common welfare of citizens in the urban century.

Tropical high Andean cities are established in soils with Andean characteristics and native ecosystems disturbed by anthropic action; the traces left by these formerly natural landscapes are still an important factor in the environmental characterization of the city. These considerations, little explored in 20th century urban management, would prove to be a cornerstone in generating strategies for 21st century urban environmental management.

Our results suggest that in cities established in the tropical highlands of Latin America, a region highly vulnerable to climate variation, the promotion of strategies that include monitoring and management aimed at enhancing the storage capacity of the soil carbon stock in an urban–rural-natural gradient would have potential effects on local, regional and global climate variations.

In this sense, a short-term challenge is the development of regional monitoring networks towards improving the availability of environmental data at the local scale; the incorporation of technologies such as unmanned aerial vehicles and multispectral or LIDAR sensors; the inventory of greenhouse gases and pollution; and, above all, the development of quantitative methods that integrate the social and ecological dimensions of the complex urban system. Access to these elements and the data they generate will allow the region's cities to gradually move towards sustainability. Their omission could delay adaptation, an undesirable situation in the global context.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors would like to thank to Universidad Tecnológica Indoamérica and Corporación Ecuatoriana para el Desarrollo de la Investigación y Academia - CEDIA for the financial support given to the present research, development, and innovation work through its CEPRA program, especially for the "Resiliencia ambiental en sistemas socio-ecológicos urbanos de ciudades neo-tropicales, casos Quito y Guayaquil" fund. Mgt. Juan Yépez, Eng. Kevin Velancia, Eng. Sebastián Segura for their support in field work.

References

Al-shammary, A.A.G., Kouzani, A.Z., Kaynak, A., Khoo, S.Y., Norton, M., Gates, W., 2018. Soil bulk density estimation methods: a review. Pedosphere 28 (4), 581–596. https://doi.org/10.1016/S1002-0160(18)60034-7.

Anguelovski, I., Carmin, J.A., 2011. Something borrowed, everything new: Innovation and institutionalization in urban climate governance. Curr. Opin. Environ. Sustainability 3 (3), 169–175. https://doi.org/10.1016/j.cosust.2010.12.017.

Arnfield, A.J., 2003. Two decades of urban climate research: A review of turbulence, exchanges of energy and water, and the urban heat island. Int. J. Climatol. 23 (1), 1–26. https://doi.org/10.1002/joc.859.

Baccini, A., Goetz, S.J., Walker, W.S., Laporte, N.T., Sun, M., Sulla-Menashe, D., Hackler, J., Beck, P.S.A., Dubayah, R., Friedl, M.A., Samanta, S., Houghton, R.A., 2012. Estimated carbon dioxide emissions from tropical deforestation improved by carbon-density maps. Nat. Clim. Change 2 (3), 182–185. https://doi.org/10.1038/nclimate1354.

Bai, X., Surveyer, A., Elmqvist, T., Gatzweiler, F.W., Güneralp, B., Parnell, S., Prieur-Richard, A.H., Shrivastava, P., Siri, J.G., Stafford-Smith, M., Toussaint, J.P., Webb, R., 2016. Defining and advancing a systems approach for sustainable cities. Curr. Opin. Environ. Sustainability 23, 69–78. https://doi.org/10.1016/j.cosust.2016.11.010.

Bai, X., Dawson, R.J., Ürge-Vorsatz, D., Delgado, G.C., Salisu Barau, A., Dhakal, S., Dodman, D., Leonardsen, L., Masson-Delmotte, V., Roberts, D.C., Schultz, S., 2018. Six research priorities for cities and climate change. Nature 555 (7694), 23–25. https://doi.org/10.1038/d41586-018-02409-z.

Barkhordarian, A., von Storch, H., Zorita, E., Loikith, P.C., Mechoso, C.R., 2018. Observed warming over northern South America has an anthropogenic origin. Clim. Dyn. 51 (5–6), 1901–1914. https://doi.org/10.1007/s00382-017-3988-z.

Bonilla-Bedoya, S., 2016. Gestión de Paisajes Forestales Tropicales en la Amazonía Andina. Universidad Córdoba.

Bonilla-Bedoya, S., Lugo-Salinas, L., Mora-Garcés, A., Villarreal, A., Arends, E., Herrera, M., 2013. Piaroa shifting cultivation: temporal variability of soil characteristics and spatial distribution of crops in the Venezuelan Orinoco. Agrofor. Syst. 87 (5), 1189–1199. https://doi.org/10.1007/s10457-013-9629-6.

Bonilla-Bedoya, S., Estrella, A., Santos, F., Herrera, M.Á., 2020a. Forests and urban green areas as tools to address the challenges of sustainability in Latin American urban socio-ecological systems. Appl. Geogr. 125, 102343. https://doi.org/10.1016/j.apgeog.2020.102343.

Bonilla-Bedoya, S., Mora, A., Vaca, A., Estrella, A., Herrera, M.Á., 2020b. Modelling the relationship between urban expansion processes and urban forest characteristics: an application to the Metropolitan District of Quito. Comput. Environ. Urban Syst. 79, 101420. https://doi.org/10.1016/j.compenvurbsys.2019.101420.

Bonilla-Bedoya, S., López-Ulloa, M., Mora-Garcés, A., Macedo- Pezzopane, J.E., Salazar, L., Herrera, M.Á., 2021. Urban soils as a spatial indicator of quality for urban socio-ecological systems. J. Environ. Manage. 300, 113556. https://doi.org/10.1016/j.jenvman.2021.113556.

Breiman, L., 2001. Random forests. Machine Learning 45, 5–32. https://doi.org/10.1201/9780429469275-8.

Butzer, K., 1964. Environment and Archeology: An Introduction to Pleistocene (Issue 4).

Calaza, P., Cariñanos, P., Escobedo Montoya, F.J., Schwab, J., Tovar, G., 2018. Building green infrastructure and urban landscapes. Unasylva 69, 250.

Canedoli, C., Ferrè, C., El Khair, D.A., Padoa-Schioppa, E., Comolli, R., 2019. Soil organic carbon stock in different urban land uses: high stock evidence in urban parks. Urban Ecosystems 23 (1), 159–171. https://doi.org/10.1007/s11252-019-00901-6.

Carmin, J.A., Anguelovski, I., Roberts, D., 2012. Urban climate adaptation in the global south: planning in an emerging policy domain. J. Plann. Educ. Res. 32 (1), 18–32. https://doi.org/10.1177/0739456X11430951.

Carmona, A.M., Poveda, G., 2014. Detection of long-term trends in monthly hydro-climatic series of Colombia through Empirical Mode Decomposition. Clim. Change 123 (2), 301–313. https://doi.org/10.1007/s10584-013-1046-3.

Carrión, F., 2010. *Ciudad, memoria y proyecto*.

Carvalhais, N., Forkel, M., Khomik, M., Bellarby, J., Jung, M., Migliavacca, M., Mu, M., Saatchi, S., Santoro, M., Thurner, M., Weber, U., Ahrens, B., Beer, C., Cescatti, A., Randerson, J.T., Reichstein, M., 2014. Global covariation of carbon turnover times with climate in terrestrial ecosystems. Nature 514 (7521), 213–217. https://doi.org/10.1038/nature13731.

Chen, L., Fang, K., Wei, B., Qin, S., Feng, X., Hu, T., Ji, C., Yang, Y., Cleland, E., 2021. Soil carbon persistence governed by plant input and mineral protection at regional and global scales. Ecol. Lett. 24 (5), 1018–1028. https://doi.org/10.1111/ele.13723.

Cutler, A., & Cutler, D. R., 2012. Ensemble Machine Learning. Ensemble Machine Learning, February 2014. doi:10.1007/978-1-4419-9326-7.

Darrel Jenerette, G., Harlan, S.L., Stefanov, W.L., Martin, C.A., 2011. Ecosystem services and urban heat riskscape moderation: water, green spaces, and social inequality in Phoenix, USA. Ecol. Appl. 21 (7), 2637–2651. https://doi.org/10.1890/10-1493.1.

Davidson, E.A., Trumbore, S.E., Amundson, R., 2000. Soil warming and organic carbon content. Biogeochemistry 408 (6814), 789–790.

Edmondson, J.L., Davies, Z.G., McHugh, N., Gaston, K.J., Leake, J.R., 2012. Organic carbon hidden in urban ecosystems. Sci. Rep. 2, 1–7. https://doi.org/10.1038/srep00963.

Edmondson, J.L., Stott, I., Davies, Z.G., Gaston, K.J., Leake, J.R., 2016. Soil surface temperatures reveal moderation of the urban heat island effect by trees and shrubs. Sci. Rep. 6, 1–8. https://doi.org/10.1038/srep33708.

Eglinton, T.I., Galy, V.V., Hemingway, J.D., Feng, X., Bao, H., Blattmann, T.M., Dickens, A.F., Gies, H., Giosan, L., Haghipour, N., Hou, P., Lupker, M., McIntyre, C. P., Montluçon, D.B., Peucker-Ehrenbrink, B., Ponton, C., Schefuß, E., Schwab, M.S., Voss, B.M., Wacker, L., Wu, Y., Zhao, M., 2021. Climate control on terrestrial biospheric carbon turnover. Proc. Natl. Acad. Sci. U.S.A. 118 (8) https://doi.org/10.1073/pnas.2011585118.

Ellis, E.C., 2015. Ecology in an anthropogenic biosphere. Ecol. Monogr. 85 (3), 287–331. https://doi.org/10.1890/14-2274.1.

Escobedo, F.J., Adams, D.C., Timilsina, N., 2015. Urban forest structure effects on property value. Ecosyst. Serv. 12, 209–217. https://doi.org/10.1016/j.ecoser.2014.05.002.

FAO, 2015. The State of Food and Agriculture 2015. Social Protection and Agriculture: Breaking the Cycle of Rural Poverty. in: *Fao*. http://www.fao.org/documents/card/en/c/ab825d80-c277-4f12-be11-fb4b384cee35/.

Forman, R.T.T., 2014. Urban ecology: Science of cities. In: Urban Ecology: Science of Cities. Cambridge University Press. https://doi.org/10.1017/CBO9781139030472.

Friedlingstein, P., Jones, M., O'Sullivan, M., Andrew, R., Hauck, J., Peters, G., Peters, W., Pongratz, J., Sitch, S., Le Quéré, C., Bakker, D., Canadell, J., Ciais, P., Jackson, R., Anthoni, P., Barbero, L., Bastos, A., Bastrikov, V., Becker, M., Zaehle, S., 2018. Global Carbon Budget 2016 Global Carbon Budget 2016. Earth Syst. Sci. Data 11, 2141–2194.

Galindo, G.G., Bingham, F.T., 1977. Homovalent and Heterovalent Cation Exchange Equilibria in Soils with Variable Surface Charge. Soil Sci. Soc. Am. J. 41 (5), 883–886. https://doi.org/10.2136/sssaj1977.03615995004100050014x.

García, M., 2018. Análisis de Sensibilidad Mediante Random Forest. In *Escuelta Técnica Superirior Ingenieros Industriales (UPM)*. http://oa.upm.es/53368/1/TFG_MARTA_GARCIA_RUIZ_DE_LEON.pdf.

Gerrish, E., Watkins, S.L., 2018. The relationship between urban forests and income: A meta-analysis. Landscape Urban Plann. 170 (April), 293–308. https://doi.org/10.1016/j.landurbplan.2017.09.005.

Giardina, C.P., Ryan, M.G., 2000. Evidence that decomposition rates of organic carbon in mineral soil do not vary with temperature. Nature 404 (6780), 858–861. https://doi.org/10.1038/35009076.

Goldewijk, K.K., Beusen, A., Doelman, J., Stehfest, E., 2017. Anthropogenic land use estimates for the Holocene - HYDE 3.2. Earth Syst. Sci. Data 9 (2), 927–953. https://doi.org/10.5194/essd-9-927-2017.

Greenstein, R., & Smolka, M., 2000. Forces, Consequences, and Policy Responses. in: Land Lines (Issue November).

Hart, M.A., Sailor, D.J., 2009. Quantifying the influence of land-use and surface characteristics on spatial variability in the urban heat island. Theor. Appl. Climatol. 95 (3–4), 397–406. https://doi.org/10.1007/s00704-008-0017-5.

Hengl, T., & Macmillan, R. A., 2019. Predictive Soil Mapping with R. in: Predictive soil mapping with R. www.soilmapper.org.

Hengl, T., Heuvelink, G.B.M., Kempen, B., Leenaars, J.G.B., Walsh, M.G., Shepherd, K.D., Sila, A., MacMillan, R.A., Mendes de Jesus, J., Tamene, L., Tondoh, J.E., 2015. Mapping soil properties of Africa at 250 m resolution: Random forests significantly improve current predictions. PLoS ONE 10 (6), e0125814. https://doi.org/10.1371/journal.pone.0125814.

Hengl, T., Nussbaum, M., Wright, M.N., Heuvelink, G.B.M., Gräler, B., 2018. Random forest as a generic framework for predictive modeling of spatial and spatio-temporal variables. PeerJ 6, e5518. https://doi.org/10.7717/peerj.5518.

Herzog, S., Martinez, R., Jorgensen, P., & Tiessen, H., 2011. Climate Change and Biodiversity in the Tropical Andes.

Hintz, A., Dencik, L., Wahl-Jorgensen, K., 2017. Digital citizenship and surveillance society: Introduction. Int. J. Commun. 11, 731–739.

Hobbie, S.E., Grimm, N.B., 2020. Nature-based approaches to managing climate change impacts in cities. Philos. Trans. R. Society B: Biol. Sci. 375 (1794), 20190124. https://doi.org/10.1098/rstb.2019.0124.

Huygens, D., Boeckx, P., Van Cleemput, O., Oyarzún, C., Godoy, R., 2005. Aggregate and soil organic carbon dynamics in South Chilean Andisols. Biogeosciences 2 (2), 159–174. https://doi.org/10.5194/bg-2-159-2005.

Kaplan, J.O., Krumhardt, K.M., Ellis, E.C., Ruddiman, W.F., Lemmen, C., Goldewijk, K.K., 2011. Holocene carbon emissions as a result of anthropogenic land cover change. Holocene 21 (5), 775–791. https://doi.org/10.1177/0959683610386983.

Kerr, D.D., Ochsner, T.E., 2020. Soil organic carbon more strongly related to soil moisture than soil temperature in temperate grasslands. Soil Sci. Soc. Am. J. 84 (2), 587–596. https://doi.org/10.1002/saj2.20018.

Klein Goldewijk, K., Beusen, A., Janssen, P., 2010. Long-term dynamic modeling of global population and built-up area in a spatially explicit way: HYDE 3.1. Holocene 20 (4), 565–573. https://doi.org/10.1177/0959683609356587.

Liu, X., Hu, G., Chen, Y., Li, X., Xu, X., Li, S., Pei, F., Wang, S., 2018. High-resolution multi-temporal mapping of global urban land using Landsat images based on the Google Earth Engine Platform. Remote Sens. Environ. 209 (February), 227–239. https://doi.org/10.1016/j.rse.2018.02.055.

Lorenz, K., Lal, R., 2009. Biogeochemical C and N cycles in urban soils. Environ. Int. 35 (1), 1–8. https://doi.org/10.1016/j.envint.2008.05.006.
Luederitz, C., Brink, E., Gralla, F., Hermelingmeier, V., Meyer, M., Niven, L., Panzer, L., Partelow, S., Rau, A.L., Sasaki, R., Abson, D.J., Lang, D.J., Wamsler, C., von Wehrden, H., 2015. A review of urban ecosystem services: Six key challenges for future research. Ecosyst. Serv. 14, 98–112. https://doi.org/10.1016/j.ecoser.2015.05.001.
Manuel-Navarrete, D., Morehart, C., Tellman, B., Eakin, H., Siqueiros-García, J.M., Hernández Aguilar, B., 2019. Intentional disruption of path-dependencies in the Anthropocene: Gray versus green water infrastructure regimes in Mexico City, Mexico. Anthropocene 26, 100209. https://doi.org/10.1016/j.ancene.2019.100209.
Masson, V., Lemonsu, A., Hidalgo, J., Voogt, J., 2020. Urban climates and climate change. Annu. Rev. Environ. Resour. 45 (1), 411–444. https://doi.org/10.1146/annurev-environ-012320-083623.
Merriman, L.S., Moore, T.L.C., Wang, J.W., Osmond, D.L., Al-Rubaei, A.M., Smolek, A.P., Blecken, G.T., Viklander, M., Hunt, W.F., 2017. Evaluation of factors affecting soil carbon sequestration services of stormwater wet retention ponds in varying climate zones. Sci. Total Environ. 583, 133–141. https://doi.org/10.1016/j.scitotenv.2017.01.040.
Morel, J.L., Chenu, C., Lorenz, K., 2015. Ecosystem services provided by soils of urban, industrial, traffic, mining, and military areas (SUITMAs). J. Soils Sediments 15 (8), 1659–1666. https://doi.org/10.1007/s11368-014-0926-0.
Nelson, D., & Sommers, L., 1996. Total Carbon, Organic Carbon, and Organic Matter. in: D. Sparks, A. Page, P. Helmke, R. Loeppert, P. Soltanpour, M. Tabatabai, C. Johnston, & M. Sumner (Eds.), Methods of Soil Analysis: Part 3 Chemical Methods, 5.3 (Issue 5, p. 53711).
Njeru, C.M., Ekesi, S., Mohamed, S.A., Kinyamario, J.I., Kiboi, S., Maeda, E.E., 2017. Assessing stock and thresholds detection of soil organic carbon and nitrogen along an altitude gradient in an east Africa mountain ecosystem. Geoderma Regional 10, 29–38. https://doi.org/10.1016/j.geodrs.2017.04.002.
Nussbaum, M., Spiess, K., Baltensweiler, A., Grob, U., Keller, A., Greiner, L., Schaepman, M.E., Papritz, A., 2018. Evaluation of digital soil mapping approaches with large sets of environmental covariates. Soil 4 (1), 1–22. https://doi.org/10.5194/soil-4-1-2018.
Olson, R.S., La Cava, W., Mustahsan, Z., Varik, A., Moore, J.H., 2018. Data-driven advice for applying machine learning to bioinformatics problems. Pacific Symposium Biocomput. (212669), 192–203. https://doi.org/10.1142/9789813235533_0018.
Ordoñez-Barona, C., Devisscher, T., Dobbs, C., Aguilar, L.O., Baptista, M.D., Navarro, N. M., da Silva Filho, D.F., Escobedo, F.J., 2020. Trends in Urban Forestry Research in Latin America & The Caribbean: A Systematic Literature Review and Synthesis. Urban For. Urban Greening 47. https://doi.org/10.1016/j.ufug.2019.126544.
Pabón-Caicedo, J.D., Arias, P.A., Carril, A.F., Espinoza, J.C., Borrel, L.F., Goubanova, K., Lavado-Casimiro, W., Masiokas, M., Solman, S., Villalba, R., 2020. Observed and projected hydroclimate changes in the Andes. Front. Earth Sci. 8 (March), 1–29. https://doi.org/10.3389/feart.2020.00061.
Patri, A., Patnaik, Y., 2015. Random forest and stochastic gradient tree boosting based approach for the prediction of airfoil self-noise. Procedia Comput. Sci. 46 (May), 109–121. https://doi.org/10.1016/j.procs.2015.02.001.
Pettorelli, N., Vik, J.O., Mysterud, A., Gaillard, J.M., Tucker, C.J., Stenseth, N.C., 2005. Using the satellite-derived NDVI to assess ecological responses to environmental change. Trends Ecol. Evol. 20 (9), 503–510. https://doi.org/10.1016/j.tree.2005.05.011.
Poeplau, C., Vos, C., Don, A., 2017. Soil organic carbon stocks are systematically overestimated by misuse of the parameters bulk density and rock fragment content. Soil 3 (1), 61–66. https://doi.org/10.5194/soil-3-61-2017.
Potere, D., Schneider, A., Angel, S., Civco, D.L., 2009. Mapping urban areas on a global scale: Which of the eight maps now available is more accurate? Int. J. Remote Sens. 30 (24), 6531–6558. https://doi.org/10.1080/01431160903121134.
Pouyat, R. V., Szlavecz, K., Yesilonis, I. D., Groffman, P. M., & Schwarz, K., 2015. Chemical, Physical, and Biological Characteristics of Urban Soils. 0129, 119–152. doi:10.2134/agronmonogr55.c7.
Pouyat, R., Groffman, P., Yesilonis, I., Hernandez, L., 2002. Soil carbon pools and fluxes in urban ecosystems. Environ. Pollut. 116 (SUPPL. 1), 107–118. https://doi.org/10.1016/S0269-7491(01)00263-9.
Prasad, A.M., Iverson, L.R., Liaw, A., 2006. Newer classification and regression tree techniques: Bagging and random forests for ecological prediction. Ecosystems 9 (2), 181–199. https://doi.org/10.1007/s10021-005-0054-1.
Quan, Z., Valdez, E.A., 2018. Predictive analytics of insurance claims using multivariate decision trees. Dependence Modeling 6 (1), 377–407. https://doi.org/10.1515/demo-2018-0022.
Rovira, P., Romanyà, J., Rubio, A., Roca, N., A. J. A. & V. V. R., 2007. Estimación del carbono orgánico en los suelos peninsulares españoles. *El Papel de Los Bosques Españoles En La Mitigación Del Cambio Climático*, *January*, 197–222.
Schneider, A., Friedl, M.A., Potere, D., 2010. Mapping global urban areas using MODIS 500-m data: new methods and datasets based on "urban ecoregions". Remote Sens. Environ. 114 (8), 1733–1746. https://doi.org/10.1016/j.rse.2010.03.003.
Seto, K.C., Güneralp, B., Hutyra, L.R., 2012. Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. PNAS 109 (40), 16083–16088. https://doi.org/10.1073/pnas.1211658109.
Shoji, S., Nanzyo, M., Dahlgren, R., 2015. Volcanic Ash Soils. Analisis Standar Pelayanan Minimal Pada Instalasi Rawat Jalan di RSUD Kota Semarang. Elsevier.
Terán-Valdez, A., Cuesta, F., Pinto, E., & Perlavo, M., 2019. Los bosques del noroccidente de Pichincha: una mirada profunda a los pulmones de Quito.
USDA-NRCS. (2019). Soil Bulk Density/Moisture/Aeration.
Vaysse, K., Lagacherie, P., 2015. Evaluating Digital Soil Mapping approaches for mapping GlobalSoilMap soil properties from legacy data in Languedoc-Roussillon (France). Geoderma Regional 4, 20–30. https://doi.org/10.1016/j.geodrs.2014.11.003.
Zambrano-Barragán, C., Zevallos, O., Villacís, M., & Enríquez, D., 2011. Quito's Climate Change Strategy: A Response to Climate Change in the Metropolitan District of Quito, Ecuador. Resilient Cities, 515–529. doi:10.1007/978-94-007-0785-6_51.