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A Composite framework for analysis of Urban Quality – a case study of Milan

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Abstract:

Commencing global discourse post first industrial revolution, from global warming, ozone layer depletion, to the broader umbrella of Climate change, the state of emergency is apparently escalating. Climate adaptation, sustainability and resilience are fundamental for urban planning transition and assessing the urban environmental predisposition is primary. Various research methodologies employ a system of quantitative and qualitative indicators to outline existent conditions, spanning across themes of socio-economic, ecological and physical characteristics of assessing the urban environment quality. However, the acquisition of qualitative indicators enumerating perceived conditions is a ground-up tedious and time-consuming process to scale up to the metropolitan level to bring to light contingent issue for policy discourse and strategic interventions. Building on the conceptual thematic domains integrating parametric indicator from census, real-estate agencies, building energy efficiency certifications database, remote-sensing and bridging the pertinent gap by assimilating insights from social media sensing into a composite framework of Environment Quality Index (EQI) for the metropolitan city of Milan at the urban scale forms the crux of this investigative study.

This has been accomplished with a set of ten parametric variables: the socio- economic indicators-Population density (PD), Household density (HD), Residential Property values (R.P.Val.), Urban Functional Diversity (UFD). The bio-physical indicators- Normalized difference Vegetation Index(NDVI), Normalized difference Water Index(NDWI), Modified Normalized difference Built-up index (MNDBI) and Land surface temperature (LST). Ecological indicators-Building Energy Efficiency Ratings (BEER) and sentiment analysis of urban public greenspaces from user-generated Google map reviews encapsulating the experiential perception of urban public parks and garden quantitatively and subsequently deconstructing the context of the reviews as supplementary to the interpretation of those sentiment score. The variables are integrated through GIS based methodology with the census block as the unit of analysis, the google map reviews are extracted deploying Selenium, text processed using NLTK (Natural Language Toolkit), sentiment analysis with TextBlob and topic modelling in Gensim all written in python. Consequently, the causality among the parametric indicators is explored through statistical correlation and regression and finally critical areas for requalification and interventions requisites are punctuated according to their priority.

Keywords: Environment Quality Index (EQI), Milan, Population density, Housing density, Remote sensing, Building Energy Efficiency class, Residential Property values, Google map reviews, Sentiment analysis and Topic Modelling.

Astratto:

Il discorso globale che si è aperto dopo la prima rivoluzione industriale, dal riscaldamento globale, all'esaurimento dello strato di ozono, fino al più ampio ombrello del cambiamento climatico, sembra che lo stato di emergenza si stia intensificando. L'adattamento al clima, la sostenibilità e la resilienza sono fondamentali per la transizione urbanistica e la valutazione della predisposizione ambientale urbana è primaria. Diverse metodologie di ricerca impiegano un sistema di indicatori quantitativi e qualitativi per delineare le condizioni esistenti, spaziando tra i temi delle caratteristiche socio-economiche, ecologiche e fisiche per valutare la qualità dell'ambiente urbano. Tuttavia, l'acquisizione di indicatori qualitativi che enumerano le condizioni percepite è un processo che richiede tempo e fatica, da scalare a livello metropolitano per portare alla luce questioni contingenti per il discorso politico e gli interventi strategici. La costruzione di domini tematici concettuali che integrano indicatori parametrici provenienti da censimenti, agenzie immobiliari, database di certificazioni di efficienza energetica degli edifici, telerilevamento e che colmano il divario pertinente assimilando le intuizioni del social media sensing in un quadro composito di Indice di Qualità Ambientale (EQI) per la città metropolitana di Milano alla scala urbana costituisce il punto cruciale di questo studio investigativo.

Ciò è stato realizzato con un insieme di dieci variabili parametriche: gli indicatori socio-economici- Densità di popolazione (PD), Densità di famiglie (HD), Valori immobiliari residenziali (R.P.Val.), Diversità funzionale urbana (UFD). Gli indicatori biofisici- Indice di vegetazione normalizzato (NDVI), Indice di acqua normalizzato (NDWI), Indice di accumulo normalizzato modificato (MNDBI) e Temperatura della superficie del suolo (LST). Indicatori ecologici-Building Energy Efficiency Ratings (BEER) e analisi del sentiment degli spazi verdi pubblici urbani a partire dalle recensioni generate dagli utenti su Google map, che incapsulano la percezione esperienziale dei parchi pubblici urbani e dei giardini in modo quantitativo e successivamente decostruiscono il contesto delle recensioni come supplemento all'interpretazione di questi punteggi del sentiment. Le variabili sono integrate attraverso una metodologia basata sul GIS con il blocco di censimento come unità di analisi, le recensioni su google map sono estratte con Selenium, il testo è elaborato con NLTK (Natural Language Toolkit), l'analisi del sentiment con TextBlob e la modellazione dei topic in Gensim, tutti scritti in python. Di conseguenza, la causalità tra gli indicatori parametrici viene esplorata attraverso la correlazione statistica e la regressione e, infine, le aree critiche da riqualificare e i requisiti degli interventi vengono scanditi in base alla loro priorità.

Parole chiave: Indice di qualità ambientale (EQI), Milano, densità di popolazione, densità abitativa, telerilevamento, classe di efficienza energetica degli edifici, valori immobiliari residenziali, recensioni su Google map, Sentiment analysis e Topic Modelling.

1.Introduction :

Urban growth as is constant process where the urban geography is thrusted into state of dynamic transformation shaped by the ever evolving economic and technological trends. The repercussions of which have resulted in degradation of spaces, pollution, congestion, inequalities in healthcare and well-being. Thus, quality assessment approaches to the urban environment evolved as measures of urban performance, set forth for policy discourses and interventions ameliorate environmental issues. Urban environmental quality is a multi-layered concept, its manifestations in research and policy decisions is rarely uniform as the underlying theoretical approaches to defining environmental quality of the study area vary. The most common quality studies are based on thematic conceptualization of "Environmental quality', 'Livability' and 'Quality of life'(Van Kamp et al., 2003).

1.1.Shared terms for spatial qiality:

'Environmental quality' is representative of the degree of satisfaction associated with the physical, social or aspect of the environment. That which generically describes the urban physical, spatial and socio- economic condition, representing one aspect of quality of life focused on the physical and material urban conditioning and its influence of human health requirement and continuation (Faisal and Shaker, 2017: Marans, R.W., Couper, M., 2000). 'Livability' focuses on both the inherent attributes of the environment in conjunction with the behavioral function of needs satisfaction, perception of habitat attractiveness in human beings as a collective and individual function. In a sense it's the convergence of environmental and personal characteristics determining to what degree the space is habitable (Pacione, 1990; Veenhoven, 1996; Newman, 1999). 'Quality of life' refers to conceptions of personal life satisfactions as it is shaped by immaterial and material entities of the physical, social, economic and cultural in the environment. In relation to individual autonomy in religious and social ethical expressions, potential realization and success in achieving mile stones in life (Cheung, 1997; WHO-QOL Group, 1993; Szalai, 1980; Diener and Suh,1997)(Garau and Pavan, 2018).

Thus, with respect to these definitions our focus is on the analysis of the 'Environmental Quality (EQ)'. The performance of an object demonstrates the magnitude of its quality and in case of complex system as an urban environment is, its quality is summarized as the aggregated of each of its components. Hence the urban environment can be described to be composed of a 'socio- economic' – infer the social consequence of economic processes (Land, 2017 ,'Bio-physical variables'– characterized by bio- physical phenomena obtained through remote sensing processes(Jensen, 1983) and 'Ecological variables – depictive of interactive process of influence, an inter play of balancing states of equilibrium(Desmond S . Cartwright, 1969). Literature studies on environment quality employ various parametric variables as indicators of quality assessment either focusing of one dimension or a composite framework or all three.

1.2.Brief overview of environmental quality assessment frameworks and types of indicators employed :

(Faisal and Shaker, 2017) Bio-physical Indicators: Land Surface temperature (LST) employed in studying surface- atmospheric energy exchanges, heat island effects and urban expansions affecting urban climate, Normalized Difference Vegetation Index (NDVI)- monitor vegetation cycles for the supply of food resource, Normalized Difference Water Index (NDWI)- measuring access to clean water resources, Normalized Difference Built-up Index(NDBI) and built-up area representing spatial distribution of intensity of the built form. Socio- economic Indicators: Population density and Building density as contributors of urban heat island effect, education and family income attributes to the ability of material investment of spatial management. Ecological Indicators: Land use and land cover for monitoring the extent of depletion of natural resources as a result of unregulated planning to ensure sustainability.

Air and noise pollution depending of transport model use, vegetation and parks, public transportation to access private mobility ownership and its implicit impacts on carbon emissions and its depending on the mobility choice an insight into the communal networking opportunity in the public realm could be synthesized. Historical areas and Central Business District(CBD) in cities generally are characterized by high density, mixed land use and typically enjoy better infrastructural managements. Sports areas, Religious and cultural zones, shopping centers, educational institutions, entertainment zones and open spaces like parks, squares located amidst dense built forms punctual outbreaks of vibrancy social and natural element interplay regulation micro- climatic comfortability.

While, crime rate exposure creates an atmosphere of anxiety, uncertainty and treat to safety to human's primal instinct and thus abandon movement in and around those areas with this attribute, health conditions Areas close to water bodies and land values indicative of spatial regulation based of certain philosophical approaches stemming from certain ideals of aesthetics and functional value.

(Messer et al., 2014) Bio-physical Indicators an Environmental Quality Index (EQI) developed as an aggregate of Air, water and land domains with various indicators reflective of quantification of pollutants concentration in the respective domains across to access contamination and toxicity exposure level inferred through the index. (Stossel, Kissinger and Meir, 2015) Bio-physical Indicators: radiation, surface Water body contamination with fecal coliforms, presence of phosphorous that indicate eutrophication conditions, and monitor Bio-chemical Oxygen Demands (BOD), concentration of pollutants like zinc, iron, copper, chromium, lead in drinking water and its turbidity. Air quality measuring the concentration of ozone, Sulphur dioxide, Nitrogen dioxide, carbon monoxide and Particulate Matter (PM10). Ecological Indicators: noise, open spaces availability. Solid waste management percentage of buildings with access to sewage systems.

(Liang and Weng, 2011) Bio-physical Indicators: Land use and cover, Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Normalized Difference Built-up Index (NDBI) and Socio- economic Indicators: population density, median age population, households, house units, vacant house units, owner-occupied house units, median family income, per capita income, percentage of families under poverty, unemployment rate and percentage of college graduated. (Nichol et al., 2006) Bio-physical Indicators: a detailed micro scale EQI assessment remote sensing application for assessing vegetation cover and vegetation density from NDVI, for air quality (NO2, NO, O3) and urban surface temperatures temperature

(De Deus, Garcia Fonseca and De Marcelhas E Souza, 2013) Socio- economic Indicators: percentage of households with trees in the vicinity; percentage of households with open sewers in the vicinity, percentage of households with garbage accumulated in the vicinity, average income of households, average income of household heads, percentage of household heads without income, percentage of literate people with more than 5 years of age, percentage of literate household heads, population density, residential density, percentage of area covered by vegetation (NDVI); percentage of area covered by artificial surfaces (NHFD); average NDVI (NDVI); average NHFD. (Li, 2014) Focused on a single issued based bio-physical Indicators: Petroleum in marine water bodies.

(Myrtho Joseph , Fahui Wang, 2014) Ecological Indicators: greenness, traffic induced air pollution, traffic induced noise, water body pollution, coastal pollution. Built environment exposure to public market and cemeteries through measurement of their respective distances, natural hazards river flooding risk, landslide susceptibility and coastal surge risk all indicators assessed in terms of the building and housing densities and distance from exposure sites.

(Nichol and Wong, 2009) Bio-physical Indicators: Heat-island intensity, vegetation density and air quality in terms of aerosol optical depth O3, Nitrogen oxides NO, NO2, NO3, volatile organic compounds (VOC), Socio- economic Indicators: building height, building density and Ecological indicator: noise. (Sruthi Krishnan and Mohammed Firoz, 2020) Bio-physical Indicators: LST, NDVI, slope – coastal region, meteorological – precipitation, temperatures, relative humidity, wind speeds, Socio-economic indicators: of population density, household density, percentage literacy rate, percentage of workforce participation.

(Musse, Barona and Santana Rodriguez, 2018) focused on bio-physical Indicators: LST, NDVI, Soil Adjusted Vegetation Index (SAVI), NHI NDWI, NDBI, NDISI, Socio-economic indicators: population density, housing density and Ecological indicators: housing values, water aqueduct percentage, Sewage percentage, Waste percentage. (Gunawan, Armitage and James, 2012) Bio-physical Indicators: NDVI, NDBI, LST. Ecological indicators: building height and distance to water bodies linked to attractiveness.

(Rahman et al., 2011) analyzed ecological indicator: built up areas, open spaces, Household density, Occupancy ratio, percentage of population accessible to roads, percentage of population affected from noise, percentage of population affected by open drainage. and socio-economic indicator of population density. (Phuong et al., 2021)utilized only Bio-physical Indicators: LST, NDVI, NDBI, Modified Normalized Difference Water Index (MNDWI) for analysis of environmental quality. While,(Lo, 1997) employed bio-physical Indicators: NDVI, LST and socio-economic indicators: population density, per capita income, median house values, percentage of college graduates and percentage of urban use.

(Majumder et al., 1970) located his analytical space at different dimensions of urban physicality with ecological indicator: flash flood, Water logging, Air ventilation, Quality of air (smell), Quality of air (dust particles/SPM), Tree within the area, Number of garden/parks/open spaces, Good water bodies (lake/river/ponds), Water quality (taste), Water quality (Physical Appearance), Noise outside (traffic/laud speaker), Noise inside (Human noise, radio, TV), Temperature summer), Temperature (winter),.Traffic jam, Transport availability, Transport rent (within city), Transport service system, Street condition, earthquake, cyclone, over all visual quality.

At the Neighborhood dimension with ecological indicators: water supply, centricity supply and gas supply, telephone services, Sewerage system, drainage system, sanitation, cleaning & maintenance, solid waste management, recreational facilities, educational facilities, health care & medical services, housing condition (Rent, Quality), slum & squatters, postal facilities, cyber cafe (Internet & e-mail), shopping center, parking facilities, religious places (mosque/temple),. graveyards, banking facilities, employment facilities, local security, law & order, business facilities. Finally at the Social dimension with ecological indicators of Privacy, Community feeling, Community activities, criminal activities and religious conflicts.

And Finally (Wang et al., 2017) (Jiang et al., 2015) brought to focus the use of social media text to highlight significant occurrence of air pollution.

Table.1.Environment Quality research frameworks and indicators

Author	Socio- economic indicators	Ecological indicator	Bio-physical indicator
(Faisal and Shaker, 2017)	4	18	4
(Messer et al., 2014)	12	13	35
(Stossel, Kissinger and Meir, 2015)	-	3	17
(Liang and Weng, 2011)	11	-	4
(Nichol et al., 2006)	-	-	6
(De Deus, Garcia Fonseca and De Marcelhas E Souza, 2013)	7	7	-
(Li, 2014)	-	-	1
(Myrtho Joseph , Fahui Wang, 2014)	-	26	-
(Nichol and Wong, 2009)	2	1	3
(Sruthi Krishnan and Moham-med Firoz, 2020)	4	-	7
(Musse, Barona and Santana Rodriguez, 2018)	5	2	7
(Gunawan, Armitage and James, 2012)	1	1	3
(Rahman et al., 2011)	5	-	3
(Phuong et al., 2021)	-	-	4
(Lo, 1997)	5	-	2
(Majumder et al., 1970)	-	56	-
(Wang et al., 2017	-	-	1
(Jiang et al., 2015)			1

1.2.1.Choises of EQI indicators and inference:

The choice of indicators is dependent on the local context and value judgements on the prioritization of the socio-economic systems, the urban ecology, or the physical biology. Where it concerns evaluating the structural form of the urban built and the corresponding social implications, population, building, household and housing densities were predominantly employed. However, housing values evaluations as indicative ameliorated spatial qualities is hypothetical and requires assessing the patterns shaping the real- estate market as implications of contextual socio-economic and spatial dynamics Regarding the land use dynamics of socio-spatial ecology, accessibility and opportunities to various concurrent social activities were evaluated. Some EQ frameworks employed a measure of the ecological sustainability practices in terms of water and waste resource managements systems.

Where bio-physical indicator is basically performance-based indicators, the socio-economic and ecological indicators selections are need or issue based. The extensive application of bio- physical assessment are popularized owing to its straightforward quantification of deteriorations with the advent of remote- sensing technological improvements which simplifies the process of data acquisition of such indicators especially at larger scales. Albeit with the complexities of processing the data which requires knowledge capacity. The acquisition process of socio-economic and especially the ecological indicators are subjective to locally situated occurrences of concerns in urban systems. Its identification being labor intensive, time consumptive and within the frame work of governance complexities of stakeholder agenda interplay often steps into the background. Also note that the last two authors based their assessment of air pollution from online stated accounts of detrimental spatial conditions on social media platforms. Consider the evolution of indicator choices were derived from the opportunities of data acquisition processes from traditional extensive manual surveys. Later with technological advancements in remote sensing and now internet facilitated digital social networking as a tool for a more intuitive and less redundant qualitative assessments.

Thus, the objective of this study is to propose a framework with indicators integrating all three systemic changes of the socio-economic, ecological and bio-physical while, assessing the ecological satisfactions associated one of key territorial element with the greatest influence urban life, the urban infrastructure of parks and garden space. While also assessing the role of urban green space in the bio-physical environmental impact, employing, NDVI, NDWI, MNDBI and LST valuations. Where it concerns the built environment and socio- economic ecology, habitational densities of population, household and diversity of land functional use and residential values is elaborated. Following along similar lines of previous research, as our study area's planning strategies developed and implemented interventions concerning energy efficiency and performances it is included as part of our analytical framework.

1.2.2.Aggregation of the indicators as Indices:

Principal component analysis (PCA), Analytical hierarchy process, Fuzzy evaluation technique and GIS overlay are the various methods of aggregating the parameters, of which most commonly of the UEQ studies are based on either Principal component analysis or Gis overlays. Principal component analysis is most suitable when the variable data types are continuous and multiple independent corelated variables and no dependent variable, reducing the various parameters into the most unrelated components capturing the values that contribute to maximum variance of the data(Lo, 1997). They can be represented in map format as object based (vector) principal components or image based (raster) principal components after the values are normalized(De Deus, Garcia Fonseca, and De Marcelhas E Souza, 2013). Object based PCA result are more accurate in comparison to image based PCA (Lo, 1997)(Faisal and Shaker, 2017).Analytical hierarchy method is more suitable when the parameters are assigned an inherent order informing the analysis of decision. GIS overlays method is suited to store, analyze, represent the parameters as layered map features, however does not considered correlation among the parameters (Myrtho Joseph , Fahui Wang, 2014; Rahman et al. 2011). Studies with comparative of EQI assessments with PCA (both vector and raster) and GIS overlay concluded the later to hold more accuracy. Thus, for the purpose of this study GIS overlays method is used, as the parametric variables employed are both discrete and continuous (Faisal and Shaker, 2017).

2.Literature Review :

2.1.Quality Management :

The quality of a product is an indicative of it performance, consequently higher performance are attributed to higher quality. Quality measurements or in sense a movement was introduced by W.Edwards Demming,in 1926 at Western Electricity company's Hawthorn plant as statistical methods employed in managing and monitoring quality of manufacturing industries products and services through “ Plan-Do-Check-Act” planned process cycles. The process later was the foundational research methodology for strategic planning and assimilated into the process public sectoral planning and popularly known as Total Quality Management (TQM), Statistical Quality Control (SQC), Continuous Quality Improvement (CQI) among many others. Essential a system of constant feed backs to manage unanticipated events. The objectives of its public sector implementation were to improve efficiency of public service delivery, its quality, level of delivery and their timelines. This comes in time when urban growth complexities called for a decentralized management, the urban inhabitant's expectations became vocal and amidst knowledge intensive economic competitiveness motivation of capacity building in public sector employees was significant. Especially with the public sector being motivated by competitiveness of private and institutional evaluation of the consequences of anthropogenic activities by developing measurable factual rationale for formulating decisions.

Where in public sector the fundamental element was the client around which the quality plan and process were centered and productive efficiency of the employees was emphasized, in the public sector instituting TQM the objective was top-down structural management diffusions across all scales of governance. The main drawback in this approach of quality management in both private and public sectors is that of the leadership turnovers, their subsequent articulations of strategic visions and endogenous change resistances. The entire organizational commitment, collaboration, information diffusion and assessments of arising conflicts within the systems and its timely resolution are quintessential for success of this framework and was perceived by the people as aristocratic(Mcgowan and Taylor, 2016)(Patrick E. Connor, 1997). Also the main emphasis of performance was in terms of progress against the intended strategic goal and not the effectiveness of strategies in itself(Nyhan and Marlowe Jr., 1995).Thus this approach of quality assessment is based on objective approach of generation predominantly performance indicators and of urban processes.

2.2.The Social Indicators methodology:

Parallel to these theories regarding social trends and measurement of social change started in the 1930's. However, in 1960 the 'Social indicators' movement gained impetus born out of concerns of identifying and assessing indirect and unintended socio-economic and technological consequence of space program by the National Aeronautics and Space Administration that was not delineated as part of the objective statements nor emerged in the technological inquiries. This was carried out by the American Academy of Arts and Science who employed statistical methodologies in the anticipation of social changes. The popularity of social indicators was an innate consequence of economic growth on environmental pollution emergence with existent indicator's inability to illustrate dimensions of social life and psychological satiations.

The social indicators can be classified in three classes namely 'normative welfare indicators', 'satisfaction indicators' and 'descriptive indicators'. The 'normative welfare' indicators derive aspects of social dimensions of policy considerations where the indicator is either the target or output. However, the assumption that these indicators be a direct measure is implausible and the concept of welfare in unambiguous as the dynamics of one social process may inadvertently create another. The 'satisfaction indicators' associated with of socio-psychological attributes of expectations, happiness, fulfilment and satisfactions. The 'descriptive indicators' are indices representative of social trends and changes. Further, Social Indicators also serve as a conduit of social reporting, enrichment and forecasting trends and topics of importance. Consequence od social indicators implementations is reflected in nations census family growth surveys, occupational mobility patterns, election studies, employment and household income, educational qualification, age and sex segmentations and the like(Land, 2017)(Ferriss, 2017).

2.3.The dimensions of analysis and theme based methodologies of urban environmental quality:

The concept of 'Spatial Quality' is complex and variable associated with myriad of meanings and definitions implied by various disciplines. According to Amos Rapoport the primary problem is the defining the kind of space the quality studies are concerned with. The types of space in this can be 'designed or non- designed'. The 'designed space' are indicative of rationale and philosophy in organizational structure of spaces based on image or schema used by an individual or collective. While, 'non-designed' reflect of sacred element of space whose understanding requires knowledge of sacred writings, traditions and myths, delineating the difference between the habitable safe spaces and the dangerous world. 'Space as a symbolic manifestation' of underlying cultural imperatives of the concerned inhabitants.

'Behavioral spaces' are the behavioral setting of individuals or groups like the difference in way a child and an adult interpret and makes use of the same space is different. 'Subjective spaces' are shaped by individual's criteria based on cognitive or psychological conditioning that shapes their identification and selection of locational choices. 'Experiential or sensorial spaces' are those with immersive sensorial stimulations which can be visual, acoustic, thermal, tactile or olfactory either individual sensations or combination. Spaces of 'Involvement' or 'Manipulation' i.e. spaces where extensive spatial modifications and changes occur are experienced differently by individual involved actively or passively.

Based on meaning of spatial use: 'Cognitive or cultural spaces' are spaces of collective experiences, memory of social groups. 'Social space' a those in which spatial organization of the spaces are manifested as a result of social segregation processes wherein the experiences of a social minority class differ from its dominant social class. 'Economic space' spaces associated with financial efficiency shaped by economic trends. Spaces shaped by 'value systems' in the relative importance of public versus private domains of urban structuring, in the distinction between the perspective of the designer versus inhabitants' definition of spatial expectations. The inhabitants might prefer a large kitchen with seating areas while the designer's ideals could be distinction. The values that the public relate to defining proximity and attractiveness(Rapoport, 1970).

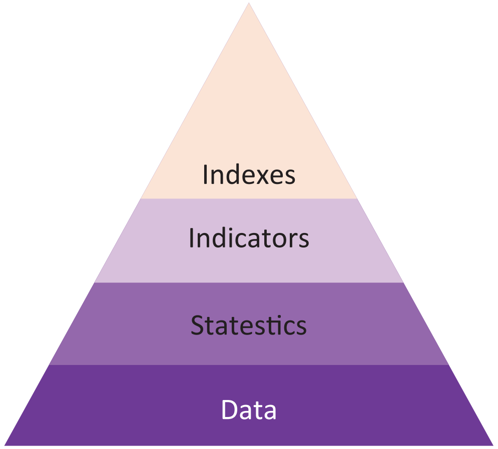
Lynch's approach is grounded in the analysis of the form and function of an urban entity as the spatial manifestation of values and needs of the society that inhabits in it. Hence, his 'five dimensions of performance' are what he believes addresses these expectations of needs and value systems. The dimensions are subdivided into concepts that resonate with the dimensions. Thus, the first dimension is 'Vitality'- sufficient supply of unadulterated natural resources for human consumption ensuring health, physical space designed for mobility safety criminologically free and an environment of parental supervision dilution over their child's accession into the public realm. While 'sense' is associated with the level of perceiving clarity of transitioning across the spatial structure of the built environment, ingraining cognizance of various elements through various sensory stimulation inferring appreciation for the space. Rendering symbolic definitions to space as a result of symbiosis of the physical space and an individual's psychological space. Hence, it depends strongly on the individual's knowledge of the space and their socio-cultural positioning that render the accessibility to this knowledge endogenously.

However, Lynch notes that shaping or reshaping the environment so as to exude sensibility is non-essential and instead could be countered by human adaptation by generation or inquisition of knowledge conferring to the meanings of the space. The 'fit' corresponds to form and functional adaptability dynamics, extent to which the form of the space stays relevant to the cultural and behavioral function requirement. 'Access' implying availability and ease of access to opportunities of social contact, employment means, basic amenities, physical and cultural activities. Finally, 'control' degree of ability of spatial modifications according to the subjective requirements. All of these are governed by meta-criteria of 'Efficiency' in terms of financial feasibility and 'Justice' in the definition of value systems of benefit distribution.

Christopher Alexander's prescription of quality which he iterates as 'the quality without a name' generated out of the symbiosis of life events and the natural space instantiated by life, with freedom of self-articulation of an individual personal space which scales-up as a lattice of intertwined spaces of events.

Jacobs and Appleyard 1987 – 'livability' related to comfortable urban habitation, 'identity and control', 'access to opportunities imagination and joy'- , 'authenticity meaning'- an understanding of the socio-economic ,cultural and spatio-structural uniqueness of different urban environments , 'community and public life'- cities as encouraging participatory activities among community members and finally 'urban self-reliance'- urban self-sufficiency in generation and consumption of resources. and 'an environment for all'- equitable access to 'livability', 'identity and control'.

Fig.1.The Data triangle



Data reflective of the multidimensional thematic variables and its sub themes are acquired, statistically analyzed for their inter relations and causality interference through exploratory data analysis and are not necessarily directed correspond to strategic interventions. They may be expressed as a collection of indicators or expressed as a linear index. According to the initial analysis the indicators are then assimilated with their individual weight's representative of their importance in the index and an overall index score is established. This is followed validation of the index either internally through evaluating the contributor indicators of the index or externally in measuring the extent of them in standing up to alternate methods. The later is typical of significance as subjective evaluations in literature have been carried out through questionnaire surveyed sample for valuation the index results. For this study the objective is limited only to the derivation of the Environmental quality index (EQI) and not its validation.

2.4.Significance of Urban Public greens:

The role of Urban greenery was brought to the foreground of urban studies when faced with the externality of industrialization, to attenuate environmental pollution and degradation, as a space for sedentary outbreak from the strenuous urban substandard lodging and working lifestyle. Since then, they have garnered immense popularity in socio-spatial research on how diverse demographic and economic stature of neighborhood residents influence park usability and their subjective experiential expectation deferring according to a child, parent, teenager and the senior aged members of the society (Deborah et.al., 2012)(Yu-Ting Chu, 2021),

the actual and perceived accessibility to parks subjectively vary with respect to spatial distribution of urban functionalities and inhabitant lifestyle and behavioral pattern. Where the closest green spaces to the residents are not the most visited and the spatial distribution of the location of parks defines its usability (Kothencz and Blaschke, 2017).The availability and satisfactory use of parks infer with the frequency and duration of visits (Veitch et al., 2021)which might not intern have significant influence on intensity of physical activity but does so promoting mental health and well-being which may reflected in their social media activities(Schwartz et al., 2019). The aspects of physical characteristic such as heath of the vegetative cover, ambient shading, landscaping, equipment like basketball courts, children's playground, clean-drinking features , events organized as means of community engagement and efficient maintenance and management of parks and its effects on popularity of parks(Haenisch, 2012),

context dependent temporality of park use behavior in its difference between weekdays and weekends to attributes of scale and distance of parks(Bertram et al., 2017), if there a question of safety concerns as an implication of the physical attributes and features if the park, size and location aesthetics of visual aspects that affects the park usage (Deborah et al.2010)(Getabalew and Alemneh, 2019). All such studies required intensive sampling and on-line or field research-based questionnaire and observational survey methodology. This can be tedious, time consuming, however aided with user generated reviews on social media platform the process is eased or slightly more channelized in the direction of actual expectations and perceptions.

2.5.Remote sensing and the urban physiology :

The science and art of obtaining information about an object, area, or phenomenon by through a device that is involved in the data collection process not being in contact with the object, area, or phenomenon under inquiry is known as remote sensing(Congalton 2015).Remote sensing finds its roots in arial photography instantiated in the 1859 and globally popularized in the Civil War.

While initially the photographs were taken from a balloon in the World War 1 aeroplanes were used. With the technological development of cameras and imaging systems such as near-infrared photography, radar, thermal sensing and Colour infrared photography the information derivation about the territorial characteristics could be obtained. In the 1940's airborne radar imaging was employed by the Great Britain in its night time military and by 1950's and 1960's university and research organisation interests in this field was evoked.

Only in the 1995 when the United States satellite-based spaces remote sensing programmes on meteorological and military observations initiated in the 1960 was disclosed that space based remote sensing garnered wide spread use. In the 1970's ERTS-1 Earth Resources Technology Satellite programme was developed and launched to collect data on earth's resources which was later renamed as Landsat in 1975. Since then over the years with many successful updated programmes with the launch of Landsat 2, 3, 4. In the 1978 earth observation programmes was launched by the French government, followed by the Russian Resurs in 1985, Indian remote sensing programmes in 1988.

The Japanese ADEOS (Advanced Earth Observing Satellite) launched in 1996 while, European Space Agency (ESA) commenced operations in 1991. The spatial resolution of all the predecessors was low though their evolution covered broader thematic analysis of land and water ecosystems. In 1999 Ikonos, QuickBird in 2001, OrbView-3 in 2003, GeoEye in 2008, WorldView-2 in 20019 with all of such launches the spatial resolution of observation has improved(Tutorial et al. 1891).

2.5.1.Vegetation monitoring:

The central epithelial layer of

the leaf the mesophyll is responsible for chlorophyl production aiding photosynthesis. The spectral index of Normalized Difference Vegetative Index (NDVI) utilizes the radiance and reflectance from RED and NIR (Near Infra- Red) channels to identify plant vegetation attributes. The Red channel locates the adsorption regions of chlorophyl while, NIR observes reflectance of vegetation canopies. This both channels are sense difference in depth of canopies (Rouse et al. 1974; Tucker 1979).

Normalized Difference Vegetative Index (NDVI) = (NIR-RED) / (NIR+RED)

The NDVI value range is -1 to +1 and classification of values to indicated various landscape aspects are derived as follows (Kriegler et al. 1969; Weier and Herring 2011)

<0.1 : barren areas and rocks,
0.2-0.3 : shrubs and grassland,
0.6-0.8 : temperate and tropical forest
0.8-0.9 : indicating Extent of healthy vegetative cover
The higher the NDVI values correspond to higher chlorophyl content in plant leaves indicative of high chlorophyl production reflective of vigorous vegetation. While, lower NDVI values identify wilting condition as a result of reduced chlorophyl production. They have also been used for track the vegetation bio mass change(Fousseni and Huang 2011) detecting decline in the natural vegetative cover due to increased agricultural and urbanizing activities in the land use. Assessing the depletion trend of natural vegetation cover through analysis of NDVI values across land use and land cover (LULC) over a temporality of a decade, highlights areas where natural vegetative areas have been converted for agricultural use and those that were urbanized (Zoungrana et al. 2018). Also employed in defining the structural attributes of urban vegetation such as crown closure, leaf area index and basal area(Ren et al. 2017) and monitoring agricultural growth across various stages in the crop cycle(Choudhary et al. 2019).

Mapping landcover changes with NDVI along with field data on tress and agricultural species in different green areas like the city park, house yards, gardens and agricultural fields has proved useful in identifying areas with requirement of vegetation interventention along the river edges to protect from flooding(Zaitunah and Sahara 2021). While, micro-scalar evaluation of NDVI and evapotranspiration data of urban landscapes are assessed to denote water stress conditions of different landcover category like the trees, shrubs, turf grass (Nouri, Beecham, and Anderson 2013). NDVI valuations are also used to monitor ecosystemic recovery of rehabilitated mining areas(Dowo and Kativu 2013) and formulation landscaping strategies for intensifying spatial distribution of tress and shrub (Bondarenko, Lyubimova, and Reshetnikova 2021).

2.5.2.Moissture and water resource monitoring:

Normalized Difference Water Index (NDWI) is employed in improved detection of aquatic features of the landscape(McFeeters 2013) and in sensing liquid moisture content availability in soil and vegetation(Gao 1996). Delineating the dimensions of surface water, it's spatio-temporal and content changes(Ali et al. 2019). The calculations of NDWI and subsequent inference vary with the methodological approaches. monitoring and managing drought prone or susceptible areas along with classification of drought intensity by analysing NDWI and Temperature Vegetation Dryness Index (TVDI) derived from NDVI to determine susceptibility of agricultural drought (Lee and Takeuchi 2021).

They are also used to derive indicators denoting water stress in crops and plan for optimal irrigation water management and distribution to critical areas and consequently, classifying crops under water stress according to their stress severity implied by a derived crop water stress index (CWSI)(Aasmi et al. 2022).Studies analysing the maintenance of urban landscape through the assessment of plant water requirement and landscape irrigation systems was carried out. It was based on the plant characteristics reflected by the NDVI and evapotranspiration conditions to identify vegetation with restricted or surplus irrigation water demand and supply dunamics. Thereby, increasing water use efficiency in irrigation management(Pedras et al. 2020).

Normalized Difference Water Index (NDWI) (Gao 1996)= (NIR-SWIR) / (NIR+SWIR)
where, Gao's version of NDWI focuses on detecting plantation water content with Short-Wave InfraRed bands (SWIR) and Near Infra-Red (NIR). The classification of the value range according to this formulation are as follows:
1--0.8 : bare soil,
-0.8--0.6 : Almost absent canopy cover,
-0.6--0.4 : very low canopy cover,
-0.2-0 : Mild-low canopy, high water stress or low canopy, low water stress,
0 - 0.2 : Average canopy cover, high water stress or mild-low canopy with low water stress,
0.2- 0.4 : Mild- high canopy cover, high water stress or average canopy cover with lower water stress,
0.4-0.6 : High canopy cover with no water stress,
0.6 – 0.8 :Very high canopy cover with no water stress,
0.8- 1 : Total canopy cover no water stress/ water logging (based on Earth Observation Systems)

McFeeter's version is employed to trace and monitor turbidity of water bodies with the Green channel enhancing the presence of water :
Normalized Difference Water Index (NDWI) (McFeeters 2013) = (GREEN-NIR) / (GREEN+NIR)
The classification of the value range are as follows:
0.2-1 : Surface water,
0.0-0.2 : Flooding or humidity,
-0.3-0.0 : Moderate drought or non-aqueous surfaces,
-1- -0.3 : Drought or or non-aqueous surfaces (based on Earth Observation Systems).

2.5.3.Built-up monitoring:

Normalized Difference Built-up index or is subsequent modification NDBI / MNDBI was designed to extract the built up areas of the landscape and consequently traces the extent of urbanization across various time frames (Zha, Gao, and Ni 2003). Monitor changes in the land use and its densities (Petrea and Moldovan 2020) and trace territorial patterns of the built and open space juxtapositions. Analysing the correlation of spatial distribution of the built-up, vegetation, water bodies and land use and land cover changes NDVI, NDWI, MNDBI with LULC(Szabó, Gácsi, and Balázs 2016) describes the state of ecological functioning of the urban systems.

Normalized Difference Built-up index (NDBI) = (SWIR-NIR) / (MIR-NIR)
For, better accuracy the index layer is stripped off the attributes of vegetation to delineated the built or impervious surfaces. Any values of the index above zero is considered to represent urbanized areas while, values lower than or equal to zero indicate open space that could either be green or blue landscape categories. However, NDBI is subjected to inaccuracies due to dry vegetation and concentration of suspended matter in water bodies which create noise and errors in identification of built-up areas hence and aggregation of the thematic indices NDBI, Modified Normalized Water Index(MNDWI) and Soil Adjusted Vegetation Index (SAVI) and their supervised classification of built-up have better accuracies(Xu 2007). Hence owing to the wide usage of NDVI and NDWI clas-

sification of land use and land cover changes with emphasis on urbanized areas the popularity and thus research using NDBI is limited.

2.5.4.Land Surface Temperates (LST) monitoring:

While the above indices are based on optical reflectance of objects, in this case elements of earth's surface, the Land Surface Temperatures (LST) are calculated based on the phenomenon of thermal radiation of the said objects. Higher the spatial agglomeration higher the Land Surface Temperatures (LST) (Kumar et al. 2021). Analysing surface temperatures of urban regions according to the LULC classes and spatial distribution of NDVI, NDWI and NDBI invariable exhibit predictable inferences (Jothimani, Gunalan, and Duraisamy 2021). The built-up impervious surfaces, baren or industrial areas have higher surface temperature values while areas with vegetation cover have lower surface temperatures(Kimuku and Ngigi 2017).

Consequently tracing urban comfort deterioration across years of anthropogenic activities with NDVI, NDBI and LST concluded that areas with increased rate of construction tends to have less vegetation cover and the more heterogeneous the vegetation landscape is the lesser the surface temperatures(Santos, Santil, and Silva, n.d.). While in general areas with high vegetation(NDVI) and surface moisture (NDWI) tend to have lower LST values(Rasul and Ibrahim 2017) (Van, Duong, and Bao 2014). Further, analysing the spatial distribution of NDVI and NDWI values implying landcover heterogeneity along with soil type data exhibits the spatial variations in surface temperatures.

The more homogenous the vegetation cover the higher correlation with LST, while higher the territorial landcover heterogeneity the lower the LST (Gu et al. 2008). Also, heterogeneity in urban spatial distribution of LST was analysed with reference to the landscape metrics and textural measure at different scales. The results indicated high correlation of LST with patch density, edge density, number of patches of the landscape metrics and energy, entropy, dissimilarity, correlation and mean of the NDVI derived landscape textures measures.

Thus, delineating various aspects of the landscape that contribute to heterogenous distribution of surface temperatures and aid in ameliorating thermal comfort with reduced surface urban heat island effect(Rahimi, Barghjelveh, and Dong 2021). Drought conditions monitoring has also been carried out using LST valuations, through derived indices of Vegetation condition Index (VCI) from NDVI and Temperature condition Index (TCI) to highlight areas of temperature related stress on vegetation(Oceanic 1995). However analysing seasonal variations of LST and NDWI values across pre-monsoon, monsoon, post monsoon and winter periods have moderate to weak correlation with NDWI(Guha, Govil, and Besoya 2020). Assessing the thermal dynamics of local climatic zones classes across seasonal variations infers spectral confusions in semi- arid regions where the surface temperatures have an inverse effect with higher LST values, due to thermal inertia of the sandy soil. while, the more low raised and compact settlement type have lower surface temperatures (Azmi, Stéphane, and Koumetio 2021). Variation in surface temperatures when observed across cities with similar urban growth from various ecological zones like the tropical rainforests, savanna derived and savanna Guinean infer the typical result.

The more urbanized an area the more it develops as a hotspot of higher surface temperatures. Particularly as urban economic growth is attributed to its population growth the densities of population along with the difference in the materiality of the urban landscape need to be explored. As different material varies in their thermal conductivity and heat capacity, analysis of the urban system from a material energy performance perspective could yield interesting insights(Ayanlade, Aigbiremolen, and Oladosu 2021).

2.6.Real-estate market regulation and the urban built :

The environment of the built encompass the human configurated materiality, biological natural landscape and social phenomenology of space. The real-estate market is indicative of certain attributes associated to a residential property as an indicator constructing attractive scenarios reflective of certain quality of lifestyle and access to amenities, opportunities and as an investment commodity for its monetary value as a rental or ownership asset. Literature spans extensive to illustrate factors that affect the valuation of both residential and commercial property extensively focusing quantitatively on the statistical deduction of supply side dynamics of social, economic, geographical, technological, and environmental factors. And a few qualitatively tracing the selection or potential selectional behavior of residential consumers through questionnaire on mail or telephone or in person interviews.

2.6.1.Accessibility to Economic transactions and employment :

Neoclassical economic theories that are centered around demand-supply dynamics of a good in this case land and residential units. Where spatial distributions of these goods depend on the cost-benefit utilization maximization of decisions makes. Von Thunen 's (1826,1966) model illustrated in his work ‘Der isolierte Staat ‘ translated as‘ The Isolated State’ based on agrarian land use economy with the market at the central spatial location. The closer a plot is located to the market the lesser its transportation cost and drive by profit maximization the higher productivity zones are located close to the market. Wingo (1961), proposed a model based on the spatial relationship between residential and work center and transportation dependance as demands that shape the spatial distribution of population in the urban fabric. Assuming that the urban structure is monocentric and at its center is the concentration of employment as the Central Business District (CBD). Consequently, both the rent and residential densities exhibit a decline from the center to the periphery. Similarly, Alonso's (1964) model bases demand as motivation to reduce the rent and transportation cost but a requisite for maximum occupiable area.

The implication of this model is a bid-rent curve with transport cost and rent as inputs. Deducing that the rich would live in lower densities in the peripheries, while the poor would live in higher densities in the center. Lowry(1964)’s model is based on the scenario where the urban economy is composed of a basic and non- basic economic sectors where, the economic development of an urban entity depends on the prime or basic economic sector. The basic sector comprises of exported goods and services, while the non-basic sector productions is utilized for the internal demands. Hence, the spatial allocation of basic sectors and its associated residential densities was determined first followed by non- basic sector. Accordingly, the urban system composition would reflect a polycentric structure of dispersed employment centers and subcenters.

The property values would be higher in areas of basic economic agglomerations than the non-basic ones. These foundational location theories infer that higher the proximity to the centers of trade and commerce opportunities results in higher property valuations(Yan Liu, 1965).

2.6.2.Accessibility to Transit :

Research evidences exhibits contrasting scenarios where it concerns proximity to public transit where on one hand due to externalities of noise, vibrations, congestion, pollution, increased travel- time and cost, expensive fares and inaccessibility the property values decline predominantly where it concerns the railway transits(McCord et al., 2018)(Anderson et.al.2010)(Andersson, Shyr and Fu, 2010)(Yu, Zhang and Pang, 2017). On the other higher transit network dependance or preference for increasing accessibility, technological improvements to transit system and higher frequency availability of transit inadvertently increases the valuations(Senior, 2009)(Gallo, 2018) (Lee, 2020)(Ibeas et al., 2012). This is observed especially in case of bus and light rail transit network where increased values are accredited to proximity(Rodríguez and Mojica, 2009). Especially the middle-income groups prefer property locations closer to these transits(Munoz-Raskin, 2010). Transit oriented Property valuation modelling have gradually evolved to include the characteristics associated with the transit hub. This include the propensity of criminal activity proliferating around the neighborhood location of the hubs and as generators of neighborhood retail activity. (Bowes and Ihlanfeldt, 2001).

2.6.3.Attributes associated with the property :

The valuation of a property especially a residential one is inherently dependent on the intrinsic characteristics of usable floor or carpet area, land area comprising the property size, nos. of bed and bath rooms, terraces, gardens, garage/ parking space, elevators, the age of the building corresponding to it aesthetic condition and energy efficiency have a positive effect of the values (Rodríguez and Mojica, 2009)(Popoola et al., 2015)(Chiarazzo et al., 2014)(Sundfors and Lind, 2017). Depending on the subjective choices of the residents according to their age, income, household composition the preference of household size, density and typologies, their selection process and trade-off reservations between their needs and willingness to pay vary the housing and rental prices. Sometime inducing trends of a preferred local characteristics like multistoried high densities or single storied low densities where in the residential choices act as generators of demand. Quality of schools, occupancy ratio of neighborhood properties, crime-rate are some of the exogenous attributes that influence property values(Aliyu and Muhammad, 2016)¬¬. Renters generate demand of mixed land use in contrary to housing owners hence, mixed land use increases the rental value in areas of pedestrian orientation than in areas of automobile dependence (Kim and Jin, 2019). Proximal availability of higher density residential developments introduced in low density areas initiates a preferential choice trend(Sodhi, Shirowzhan and Sepasgozar, 2021).

2.6.4.State Vs Private Regulations and property valuation :

The choices of the residents and the morphological character of the built and consequently the property values are further endogenously shaped by local building and zonal planning regulation. By enforcing negative prescriptive rules capping high densities, restricting supply of housing unit and plots and their efficient utilization performance through building and development codes. This effectively curbs down competition, reducing affordability resulting in lower densities of large affluent neighborhoods. It is in these type neighborhood communities where zoning regulations have the highest inclination to be followed and the least affordable capacity groups are pushed beyond the control zones. With reduced means and material access, their dwelling constructs are haphazard and of inferior aesthetic, hygiene and due to lack of planned regulations in such areas have lower property values(Todes, 2017).

Post suburbanization growth control or 'urban containment' and zoning strategy of implementing urban growth boundaries, exclusionary zoning practices leading to planned gentrifications and rehabilitations impose fiscal and social externalities, in contradiction to the physical externalities of---that. Contrary to traditional planning the bottoms-up Home Owners Association (HOA)'s self- organized spatial regulations through mutual agreements are more flexible and responsive to the local context(Ellickson, 1973; Fischel et al., 2004). Spatial implementations of such institutions also result in higher property valuation. Conclusively we could infer that presence of either kinds of land regulations are expected to raise its values as opposed to unregulated areas(Quigley et al., 2005).

2.6.5.Value addition and negations of environmental attributes :

Accessibility to scenic panorama of greenery, forest-cover and surface water bodies(Gilaninia, Dizaji and Mousavian, 2011), different types of the green areas like public and private parks, gardens, square and sports fields and their spatial densities and proportions of public greens within the built juxtaposition (Saeed and Mullahwaish, 2020), clear water of lakes (Michael, Boyle and Bouchard, 2000)along with greater access to public transit especially bus service provided, reduced noise explicitly with greater distance from suburban railway transit network and better air quality levels all imply positive contribution to residential property values(Chiarazzo et al., 2014).

Any environmental disamenity can be detrimental to the property value deterring its potential use and rate of capitalization. Be it the locational proximity, increased frequency and speculations of perceived risks to natural hazard prone zones like haze(Liu et al., 2018), earthquake(Bleich, 2003) or hurricanes(Graham, Edward and Hall, 2001), floods, fires(Nikolaos, Dimitra and Agapi, 2011) landfills zone, exposure to poor air quality, noise-pollution(McCord et al., 2018)(Ronald G. Ridker, 1967), or nuclear power plants or incinerators(Katherine A.Kiel; Katherine T.McClain, 1995). All of these are inversely related to the property values. Patchin (Patchin 1991) one of the pioneers of contaminated property research, postulates factors that contaminated real-estate value. Foremost is the 'stigma' associated with the property, defined as an investor's rationality of investment amidst risk-driver markets, 'Fear of remediation/hidden cleanup costs', 'market resistance'- how a gentrified property is perceived, 'fear of public liability' -litigation issues with future owner, 'lack of mortgeability' from the perspective of public financial institutions. Thus, followed extensive research dedicated to exploring varies methodologies in quantifying the so termed 'stigma effect'(Jackson, 2001).

2.6.6.Information and market fluctuation :

However the lack or availability of information or awareness about a disamenity or in-case of presence multiple disamenity the tradeoff among the better-off alternative choice, according to case-based theory (Itzhak Gilboa, 1995)retrospecting on their previous experience or others though bounded rationality of acquired risk losses, all account for increase or decrease of the residential values by inciting bargaining and discounts claims on the sale value (Hite, 2016). This also sees an increased duration of marketing for such residences (Jackson, 2001). In such cases intensity of operational narrative of media, public discourse, and critics are key channelers of public perceptions. The role of planning and regulatory bodies in implementing strategies and stringent policy guidelines can recuperate the real-estate market.

2.7.Social media platform as tools for urban analysis :

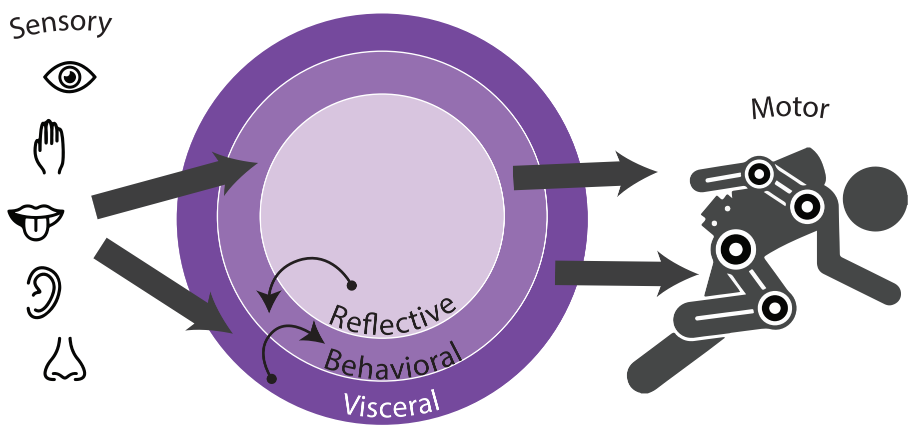
Cities have evolved from being shaped by flow of people, labor and product to flow of information and social networking platforms are a source of disseminating data worldwide instantly, allowing users to post short contents, as images and texts. It has become an essential part of our lifestyle, influencings our behavior and selection choices such as the way and what we shop, type of music or media content. These platforms also serve as touch points for business brands to understand and communicate with the demands of target consumers, assess their progress with completions and potentially retain and spread their brand value all though the online presence and communication strategies.

Literature has explored the potential of social median analytics to infer behavioral dynamic of the real worlds through the lens of their digital footprints from a basic business application such as analyzing the consumer reviews of Samsung phone on Flipkart an e- commerce website(Sheikh et al., 2021), Google Play store review data assessing the performance and user satisfaction of multiple applications on the platform, movie reviews from review aggregating website(Bonta, Kumaresh and Janardhan, 2019), assessing the polarity trend of median personalities on twitter(Kunal et al., 2018) to its potential in the educational department in reviewing the performance of Massive Open Online Coerces (MOOC)(Wu et al., 2019), or opinions on online mode education during the covid pandemic from articles and blogs on web search engines(Bhagat et al., 2021) help to explore the transitioning of the learning environment, in the medical sector where these platform serve as a source of reliable and accessible information of the efficacy of medical drugs, prescriptive treatments and treatments from the reviews of patients on healthcare forums(Saad et al., 2021).

At the urban managerial level of the Hospitality and Tourism sector, which confer significant contribution to the economic growth and standing of a city and thereby also the country. Being an intensive service sector of multi-various hedonic goods like, restaurants, themes parks(Luo et al., 2020), vacation rentals, tourist attractions and the likes, becomes imperative to assess and monitor the quality and quantity of experiences of the highly contentious user- demand driven space. In the digital age of social media, where user shared opinions and experience of places they visited becomes a reliable and detailed source of informed travel planning for succeeding visitations. Here also they have aided in mapping environmental degradation through tourist's reviews regarding their perceived the air quality (Tao et al., 2019)(Wang et al., 2017), or 'LiveCitie' a web based application visualizing the urban functional dynamics using combined data source of Facebook geo-located user profile, interested check-ins and Foursquare venues(Del Bimbo et al., 2014).

At the level of the urban socio-political landscape these platform prove useful to assess public sentiments on urban projects as in case of an airport in

Fig.2.Levels of functioning of the human brain, source: (Donald A Norman, 2004)



Mexico(López-Ornelas, Abascal-Mena and Zepeda-Hernández, 2017), understanding feedback sentiments of urban commercial and cultural service providers from google-maps(Shakhovska, Shakhovska and Veselý, 2020), or in generating urban emotion map urban inhabitants satisfaction with respect to the accessibility, perceived level of safety, functionality and spatial quality and social phenomena of urban built and landscape from foursquare location based reviews in Mexico(Lizcano and Lizcano, no date).

Further perceptions summarization from news and social media feeds are also employed in the market psych evaluations for informed strategic investment decisions as in case of Thomas Reuters Marketpsych Index(TRMI)(Peterson, 2016)

In these studies, the focus in on interpreting the sentimental value from the reviews regarding the entities under consideration for the study.

2.7.1.Understanding emotion generation and qualification methodology:

Human beings process information through a two-component system, a conscious and unconscious system aided by the preconscious as illustrated by Sigmund Freud or one with the affect or judgement system and the other the cognitive system(Donald A Norman, 2004). Elaborating on the latter, the affect system functions by providing continual information or judgement about the surrounding while the cognitive system interprets sense and meanings of the surrounding. Emotions in this sense is the conscious experience of the affect system(Ledoux and Brown, 2017)(Donald A Norman, 2004). Neuro scientist Antonio Damasio studied people with weak emotional system and otherwise perfectly normal individuals and found that they lacked proper decision-making skills. Similarly, research emphasize the significance of emotions in cognitive and behavioral functioning decision making of human beings(Markič, 2009). Our emotions are integrated with behaviors preparing the body to respond appropriately to situation through simple facial expressions, body language or fight or flight responses. A study on human emotions conducted by Donald Norman, Andrew Ortony and William Revelle professors of psychology department at Northwestern University infers that the human brain processes information according to a three-layered functioning of the brain Fig.2. The visceral layer responsible for automatic response and rapid judgement signaling the brain to control muscles taking appropriate actions based on the exposure of sensorial stimulations. It is also the lowest level of action stimulation which occurs subconsciously almost instantaneous.

The behavioral layer channels behavior subconsciously and the reflective layer is the seat of contemplation, observes and reflects on experiences. It is in the reflective level that the influence of thoughts and emotions can be perceived and ranked at the highest level. The actions of the behavioral layer can be inhibited or amplified indirectly by the reflective layer retrospecting, evolving from previous encounters and attempts to influence the behavioral layer. Brain can operate from the visceral level in a bottoms-up manner, perception induced with the affect system assigning significance or top-down from the reflective level induced by thought with the affect system and the cognitive system encompassing value and meaning. The affect system functioning is perpetual leading to a positive affect state or negative affect state which alters our thoughts. According to the nature of the affect state an individual is in either positive or negative we experience emotions appropriately.

Emotions change behavior over a short time period as a reflexive responsive lasting a few minutes or hours. While moods last longer from a couple of hours to a few days and traits last the longest from years to a lifetime developed as personalities. At the visceral level all humans are same, at the behavioral and reflective levels depending on individual education, experiences and culture with the latter being the most variable(Donald A Norman, 2004).

The concept of 'Affective computing' denoting human-computer interactions was conceived to effectively communicate user's emotions, develop software infrastructure capable to handle such information, reduce frustration associated with technology use and construct tools that enable social-emotional skill development in autistic children. The infrastructure of such data collection was not lab-based test rather accumulated from real-world expressions through wearable devices which gather facial expressions, speech and trace physiological changes induced by psychological oscillations(Picard, 2019).

Similarly, computational linguistics deals with the analysis, interpretation and modelling natural language of human-to – human communication as software application(Hausser, 1999). A feature of such analysis is sentiment or opinion mining which involves studying people's emotional valuations, state and opinions from raw natural language textual data. Extensively employed in managerial and social science applications. An 'opinion' is composed of five parts '(e, a, s, h, t)'
where,
e- is the opinion target entity,
a- is the aspect associated with the target entity,
s- sentiment of the opinion in correspondence to the target,
h- opinion holder and
t- time when the opinion is conveyed.

sentiment or opinion target is the object or entity which can be a person, product, service or an event upon which the sentiment is exhibited. Sentiment itself constitutes three parts, the type, orientation, and its intensity. Sentiment type can either be emotional or rational depending on the interaction between the visceral, behavioral and reflective levels of the opinion holder. The orientation of the sentiment is the affect state which we know can be positive, negative or in case absence of sentiment or opinion a neutral condition. The emotional sentiment is stronger that a rational one given that rationality is the expression of factual situation while emotions are associated with subjective triggers synthesized by the influence of the psychological reflections. Sentiment intensity indicates the degree of strength for example fine, good, great in order from left to right of increasing intensities. This Sentimental intensity can be discretely represented as numeric ratings for example star ratings. An such sentimental evaluations are based on the aspect of the entity under study this process is also referred to as aspect-based-sentimental analysis. It is thus that these qualitative attributes that are quantified as tools of assessments(Cambria et al., 2017).

2.8.Analytical applications of Machine learning algorithms for urban data analytics

2.8.1.Natural Language Process (NLP):

BM defines NLP as a branch of computer science along the stream of artificial intelligence that seeks to combine computational linguistics- a rules-based modelling of human language with statistics and machine learning models, so as to enable computers to process, understand and infer meaning and contexts of texts the same manner humans do. From span detection and classification of emails, text summarization, voice operated GPS systems, chatbot interface of website, text-to speech and speech to text digital assistance using speech recognition and named entity recognition are some of its most known applications. The Natural Language Tool kit (NLTK) is an opensource program that reduces the complexities of processing the various data structures, and functions unique to each language, for comprehension of multiple linguistics. It was developed by Steven Bird and Edward Loper as a part of computational linguistics course in the department of Computer and information science at the university of Pennsylvania. NLTK runs python supported windows, OS, Linux and Unix. Python an object-oriented computer language developed by Guido Van Rossum was chosen by the developers of NLTK for its shallow learning curve, rapid prototyping and testing, with easy-to-use graphic visualization libraries. (Bird, Steven, 2002)

Steps involved in NLP using NLTK program:

- Cleaning the text – to remove punctuations, icons, emojis using Substitute function to keep only elements that are words by substituting any punctuation or emojis with nothing
- Removing Stop words- stop words are the most commons words that do not possess any useful information. They help to understand the sentence structuring but not the semantics of the sentences and hence are removed.
- Text tokenization – The sentences are broken into a list of words using nltk. RegularExpression Tokenized
- Text Normalization- transforming the words into their lowercase to remove any differentiation of word according to their cases while processing.
- Stemming- reducing words to their stems stripping the prefix and suffix using nltk.PorterStemmer
- Lemmatizing- a lemmatizer removes the prefix or suffix if the remainder word is available in a language disctionary of the program hence WordNet a semantic dictionary of the English language is used for this purpose(Bird, Steven, 2009)
- The Lemmatized text is further processed to derive required or expected information.

2.8.2.Latent Dirichlet Allocation (LDA):

It is an algorithm for topic modelling of textual data, a three-level hierarchical Bayesian model based on generative statistics. Assuming each document is a 'bag of words' model composed of words each of which has a certain probability to latently represent a topic which generates it and the document may be considered to be composed of a random mixture of a few such latent topics elaborated in Fig.3. Further assuming that the topics of the document have a few sets of repetitive words. Hence the generative probability of words to belong to a certain topic in a two-level clustering model would involve a topic variable selected one for the corpus of multiple documents and once for each of it documents, where as in a three-level model the topic node is sampled repeatedly within the document.

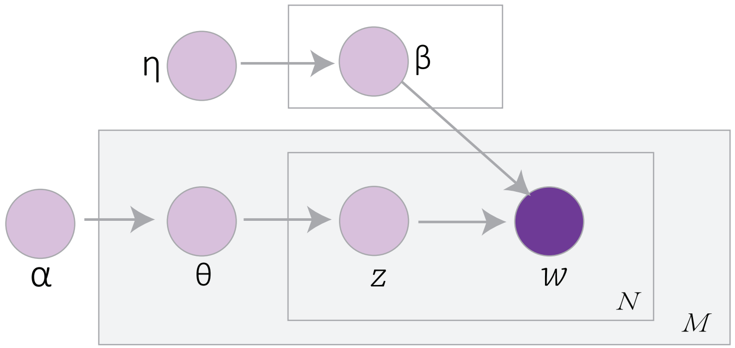
Where,

'M' –no. of documents,

'N'- no. of words in a given document say i^{th} document,

'w'- is the specific word, say jth word in i^{th} document,

Fig.3.Latent Dirichlet Allocation (LDA) model workflow:



'z'- is the topic for the jth word in document i,
'θ' – topic distribution for a document i,
'β'-word distribution for topic k,
'α' – is the parameter of the Dirichlet prior on the pre-document topic distribution

and 'η'- is the parameter of the Dirichlet prior on the per topic word distribution.
The outer plate represents the documents, and the inner plate represents the repeated choices of topics and words with in a document and smaller plate represents topics. The input data is word-document matrix resulting in a word -document -topic matrix(Blei, Ng and Jordan, 2002). LDA and topic modelling has been used to derive insights from textual reviews of theme parks (Luo et al., 2020) and hotels(Bi et al., 2019) and have proved their accuracy. cost efficiency and efficiency compared to traditional qualitative questionnaire-based research inferences.

2.8.3.Pearson's Correlation coefficient:

Statistical methods for numerical variable evaluation calculated to interpret interdependent trends among the variable analyzed, the degree to which extent their statistical relation is linear. For example, a correlation analysis between 'A' and 'B' would infer result if the values of 'A' increase then will there be any changes in the value distribution of 'B' as in will values of 'B' also increase or inversely decrease. Thus the correlation coefficient represented by 'r' has value ranges from -1.0 - +1.0. The values of r>0 positive and as the values distribution moves closer to one the more significant the inference of correlation is while, r<0 implies a negative correlation and r < 0.5-0.7 – indicate moderate correlation while, r > 0.6-0.7 – indicate a strong correlation and r<0.4 weak or no correlation. A prior correlation assessment of variable can be further quantified for their linear(Sauter, 2002).

2.8.4.Linear Regression:

It is tool that predicts the future value of a variable which is the dependent variable, considering the values or another variable- the independent variable in case of simple linear regression, or more than two variables in case of multiple linear regression. The independent variable is represented in the 'X' axis while, the dependent variable is represented in the 'Y' axis. Represented as a simple regression model $Y= \alpha+\beta X+e$ or multi-linear regression model $Y= \alpha+ \beta_0 X_0+ \beta_1 X_1+e$ as a line representing the model. Where,
Y- Dependent variable
X- Independent variable
α- intercept- a regression parameter
β- slope- a regression parameter represents how much a dependent variable will vary if the independent variable of a given beta value increase by 1 unit.
e – error term

The line of best fit of the model representing the relationship of the data points is an eyeball method such that manual tracing of the line divides the data points of both variable equally on both and the closer they are to this line the better the model is fitted and less the errors. This is mathematically represented as adjusted R or R-square values ranging from 0 to 1. Thus a R or R2 =0.9 indicates that 90% variation in the dependent variable that could be predicted by the independent variable and the more the value is toward 1 the better the relationship of the variables(Etheridge, 2010).

3.Introduction to the study area- ‘Milan’ from the perspective of planning strategies and the evolution of the cityscape and it relevance for the study :

The city of Milan is located in the low- lying Padan plain of northern Lombardia region of Italy, the economic and financial capital, is the second largest city in the country. A prominent economic center during the industrialization which transitioned post-industrial period with ease. With service, business, financial, creative, manufacturing and tourism industries ranking it the 4th highest GDP in Europe and the 6th in the world. Home to the residential population of around 1.35 million the municipality of Milan is situated in a networked poly-centrality of an number of municipalities that compose the Milan metropolitan region accommodating about 3.2 million residents. Owing to its positions as an industrial hotspot congestion, air pollution control and mobility issues are a key concern.

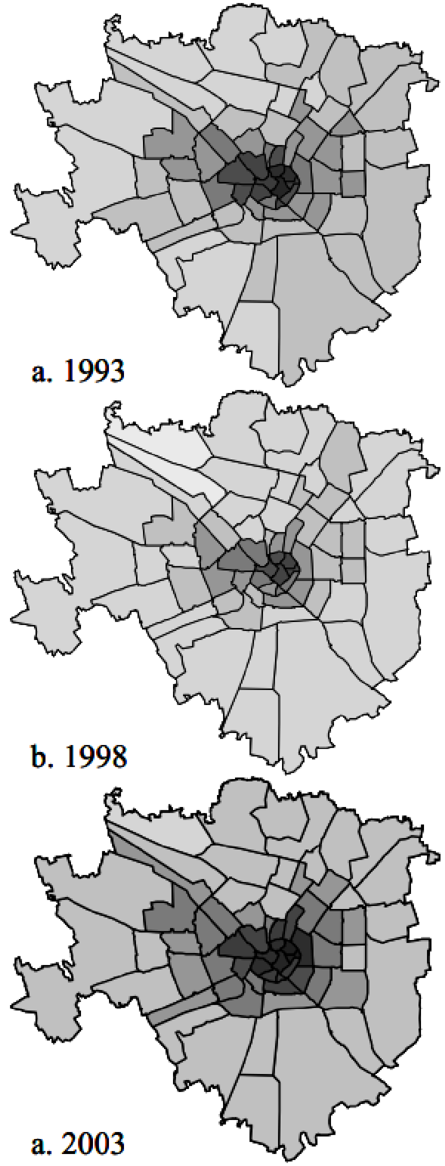
3.1.Spatial contestation and strategies through time:

The period from the 1950’s- 1970’s post-industrial scenario of industrial decentralization out and away from the urban center of Milan left in its wake the requisition of renewal of industrial built and brownfields land areas. In the 1960’s the city experienced its first gentrification process as by the inner city bourgeois interior requalification. While second rounds of gentrifications emerged in 1970’s owing to industrial decentralization engraining deep transformations in the rings of the canals and Spanish walls.

By the 1980’s- 1990’s, contextualized in an era of municipal administration under socio- political conflicts and lack of administrative hierarchical structure and insecurities in municipal autonomy in administration, followed by recession rendering urban renewal was slow. Exacerbated of technological innovations in transportation added railway derelicts to list. The General Regulatory plan (GRP) of the early 1980 implemented reservation of the industrial areas for future production and regulated small and median areas conversion, while clauses in delineating large area conversions involved complexities. This issue was rectified through Urban Renewal Programs (URPs) outlining course of developments. The major development one in the bovisa and the other near bicocca envisioned as an outcome of public-private and institutional (Politecnico di Milano and State University of Milan) partnerships were formalized instrumental use of university functions along with other projects made the third wave of gentrifications.

The former development in near bovisa was a success owing to the presence of functioning railway network and its correspondence with the nearby district plans. While, in Bicocca owing to poor public serviceability could not realize de-

Fig.4.Gentrification Waves in Milan, Source : Diappi and Bolchi, 2006



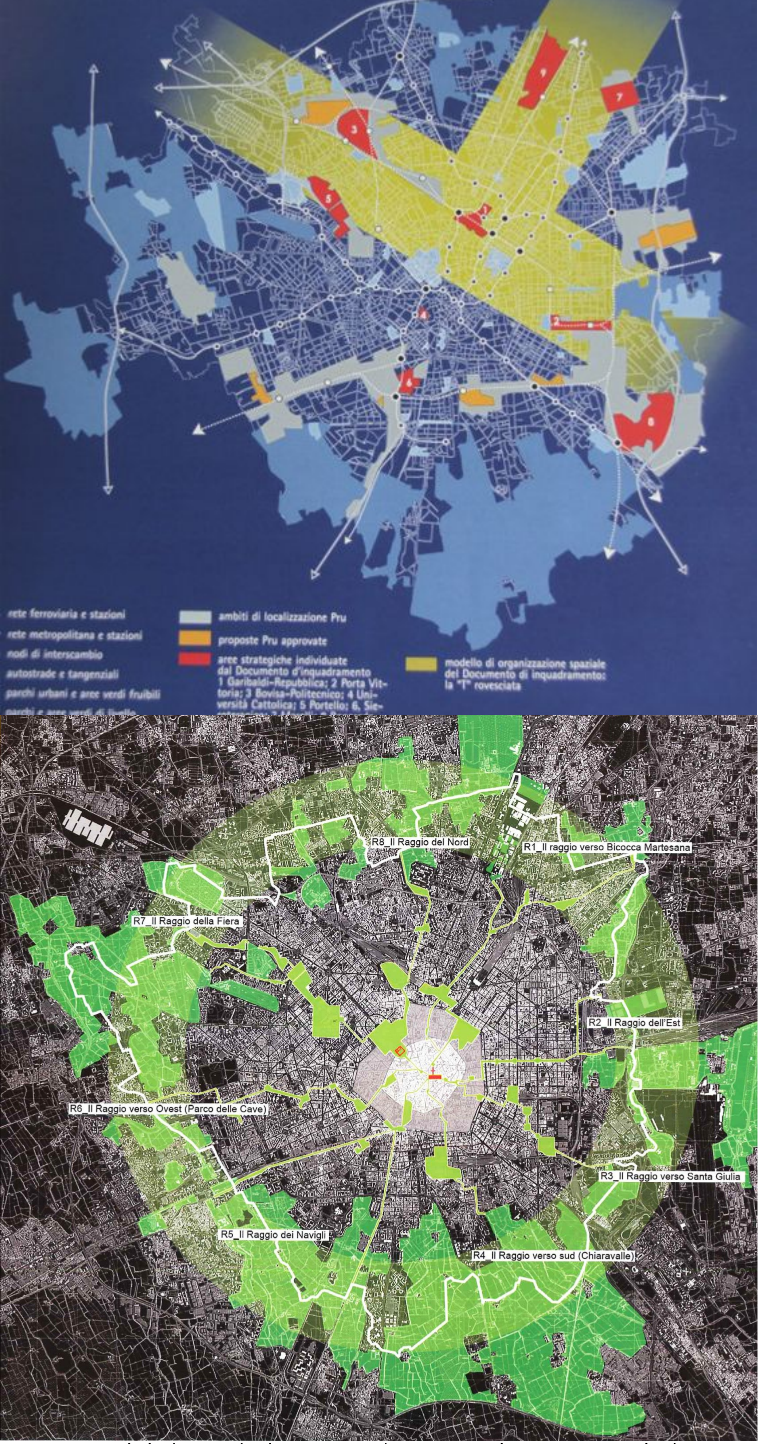


Fig.5.Top-'T' shaped planing and Bottom- 'Green River' plan

sirable results. Other similar large project like the quartier Adriano also was stuck in similar situation where construction completion stagnated. During this time at the regional level plans for the protection of features historic and environmental values was laid. This established regional parks of Parco Nord, Parco Agricolo Sud and Boscoincitta- reclamation of former abandoned agricultural areas, Rubattino and OM parks – retaining the industrial memory in its regenerated landscape acting as the green lung of the metropolis(Jiang et al., 2015). By this Milan saw the establishment of Mulitnational corporsaions. garnered international repution for fashion industry and attracted local and foreign immiration.

'Reconstructing Greater Milan' 2001 – strategizing public-private role in town planning increased economic and attractiveness of Milan. Construction developments were directed to infrastructural services like the metropolitan railway and water treatment plant while that for the residential purposes declined. As the interventions were situated in isolation the result was a urban sprawl of differing densities, around this time the resident population shrunk from 2 million to 1.6 million. Thus, for a harmonious urban landscape aesthetics a 'T'- shaped spatial ordering was implemented incorporated with parks and green areas as radiant green corridors from the city's center 'Reggi Verdi/ Green Rayes' (Trono and Zerbi, 2002) as a part of the Territorial Co-ordination Plan(Piano Territoriale di Coordinamento Provinciale-PTCP).

The Sustainable Urban Mobility Plan2016 (SUMP), carried out since 2013 focusing reducing traffic by reduction in car dependency through multi modal transport choice modelling promoting pedestrianization and bike accessibility of space, reduce exposure to air and noise pollution and improve landscape quality. Digitalized car parking and implementation of 'Area C'- congestion charge zone to ensure reduction of accidents monitor and control emission qualities(Berrini, 2016).

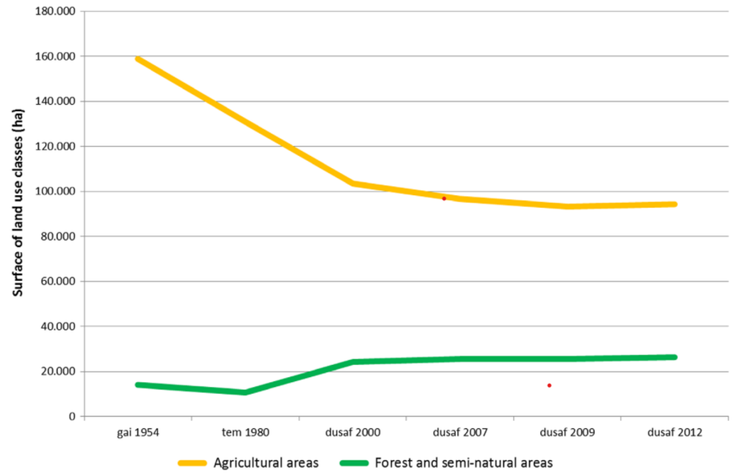
'EXPO City' in 2015 themed 'feeding the planet Energy for life title holder, Milano Urban Food Policy Pac t(MUFPP) establish commitment with over 100 cities to develop and implement sustainable food systems adopting 17 Sustainable Development Goals (SDG's) . It also enabled Milan's renewed emphasis on re-qualification for recreational spaces use resulting in redevelopment of CityLife park, Portello, Porta Nuova Area, Library of Trees and Giardino Franca Rame. As part of 'Re- shaping Milan' 2015-2018 developed in collaboration with Politecnico di Milano retrieved unused railway yards with the city limits from the Italian Railway upon the inhabitants demands for more green spaces and reduced mobility intensities. This led to the 'Fiume Verde/Green River' project of urban reforestation of 90% of the yards into a continuous system of green infrastructural landscape of diverse vegetative cover. This green infrastructure's prime role is the amelioration of air qualities through carbon sequestrations and preservation and sustenance of ecological biodiversity.

Milan adaptation strategy for 2020 'open streets'- evolving from the 2018 ' Piazze Aperte' test project on tactile urbanism application in the city now renounced to vitalize streetscapes as the extensions of public space available to restaurants as outdoor social spaces. With new bi-cycle lanes, mobility as a service bike sharing facilities, mobility bonuses to aid in purchasing and use of electric vehicular transitions incorporated with 'Citta 30 (30 km/h city)' to replace urban road network currently at 50 km/h speeds to increase safety, reduce accident and pollution cause by traffic emissions. Finally, Rediscovered neighborhood dimensions through micro scaled strategies of service accessibilities within 15- minute walking distance are all the interventions planned to aid post- pandemic lifestyle transitions(Commune di Milano, 2020).

The National Energy and Climate Plan (NECP) for 2030 focused on setting targets on 'Renewable' energy consumptions predominantly through electricity, its generation and storage. 'Energy efficiency' achievement through tax deduction schemes 'Ecobonus' in 2020, white certificate set-up for the industrial sector in 2016. While monitoring and nudging increase in residential building performance through obligatory energy certification(APE) institutionalized in 2010 .And to provide 'Energy security' by reducing consumption and diversifying energy import pipelines so at to achieve 64% emission reduction by 2050(Lombardini, 2021).

The evolution of various urban spatial strategies focused on the valorization of public green spaces, reducing emissions, promoting well-being and secure mobility, opportunities of social cohesion and enhancing the energy performance of the urban built. However, the objective of our study is centered into the evaluation of the precise aspect of assessing the energy performance of the built, urban environment comfort and sat-

Fig.6.Declination in Agricultural and Forest ares 1954- 2012, Source : Sanesi et al., 2017



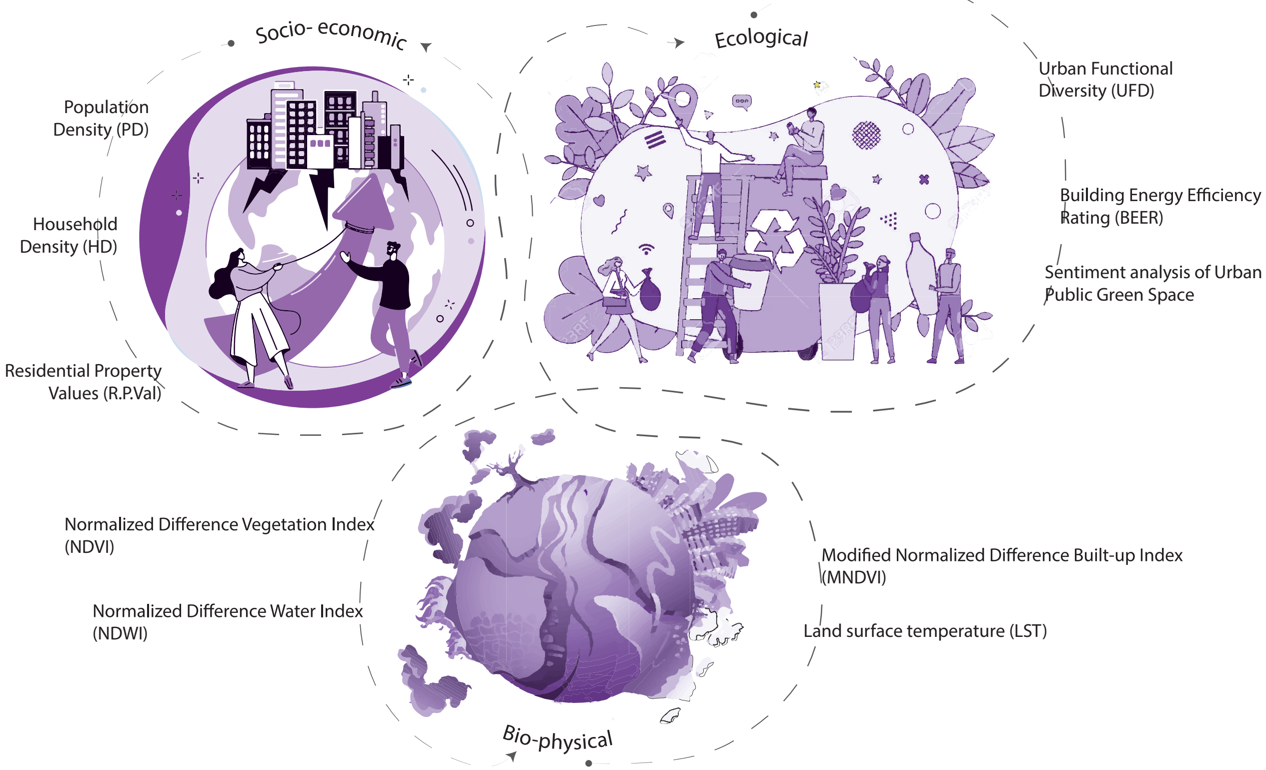
isfaction levels of public green spaces. By evaluating energy performance conformality of buildings in terms of the Energy performance Certifications (APE) in assessing the spatial implication of the performance classification. Assessing the urban landscape comfort attributed to the heterogenous spatial distribution of landscape in the built environment. While also delving into the citizen side of categorical demands associated with the public greenspace usability.

4.Methodology:

4.Structuring the Research questions, the parameters and aggregation methodology :

Quality is a complex phenomenon whose connotation depend on how various research disciplines frame the problem definition of quality analysis and the context in which it is embedded. Environmental quality studies predominantly focus on cross- cultural objective quantification data of grounded factuality of quality implications across trans-scalar systems. While subjectivity correspondence of quality studies centered around cultural and time specific emphasis on qualitative perceptions, attitudes and value systems, the complexities of which render the scope of analysis implementation to smaller neighborhood scales. The 'quality' studies preliminarily stem from private sectoral characterization of performance efficiency, productivity management and satisfaction assessment. Consequently, finding its way in urban quality management frameworks of the public sector for affective infrastructural and resource management.

Fig.7.Themes and its corresponding representative indicators :



Hence, proposed in this study is an exploratory synoptic approach on factors that contribute to environmental quality of Milan through development of a composite framework of ten indicators spanning across socio-economic, ecological and the bio-physical environment domains encapsulated in the Environmental Quality index (EQI). The socio- economic indicators-Population density (PD) and Household density (HD) are employed to reflect spatial conditions of agglomerations and are inquired for disamenity. Residential Property values (RP Val.) are employed to analyze economically induced spatial disparities, while Urban Functional Diversity (UFD) checks for variability if land uses within each block. The bio-physical indicators-Normalized difference Vegetation Index (NDVI) highlights presence of vegetative cover while, Normalized difference Water Index (NDWI) checks for surface water and water stress conditions in the vegetation. Modified Normalized difference Built-up index (MNDBI) and Land surface temperature (LST) analyzes the patterns of built-up assemblage and its associated surface temperature climatic hotspots. Ecological indicators -Building Energy Efficiency Rating (BEER) and sentiment analysis of urban public greenspaces from user-generated

Google map reviews illustrating the experiential perception of urban public parks and garden quantitatively as the measure of the review's polarities. The indicators are acquired from conventional data collection of institutional databases sources, technological advanced applications of remote sensing and explores the opportunities of social sensing the digital media space of the Google maps geo browser. We establish this analytical framework within the metropolitan city of Milan with census block group as the unit of analysis.

While, the outcome is to delineate critical areas for policy interventions and requalification strategies, each parametric indicator is analyzed as a stream of inquiry into their contribution to the quality of the urban environment and their causal relationship and implications with other indicators. The method of integration of the indicators is through GIS overlays while, process of aggregating them vary with respect to the data type of the indicators, which is illustrated in the following sections.

4.1.The socio-economic indicators:

4.1.1.The Population Density (PD) and Household Densities (HD):

The Population Density (PD) and Household Densities (HD) draws our attention to areas of concentrate habitation, overcrowded living condition scenarios and in extreme case represent degraded, substandard ghetto or the like kind of spaces. Hence, For this study we enquire primarily, how the PD and HD of Milan are disseminated across the categorical classification of spatial homogenous configuration reflective with the official real-estate agency Osservatorio Del Mercato Immobiliare as: central, semi-central, peripheral, suburban and extra urban.

To do this we observed both the average and median density values in each of the spatial classes. The PD and HD are derived from the census data ISTAT 2011. The difference between average and median values would reflect presence of outliers, a situation where within a spatial category the density values are a heterogenous mixite of high and low densities, while insignificant variance is indicative of homogenous or saturation of density across the particular spatial category. Secondarily, exploring the spatial implication of densities and transport network, as deductive examination of accessibility and preferential dependance of a particular transport mode. This is carried out assessing the relationship of PD and HD to the proximity to transportation, the bus and tram stops, the metro and the highspeed railway stations respectively.

Residential Property Values (R.P.Val.) : The real-estate market valuations in addition to economic conditions are influenced by value additions of amenities and consequently have an inverse relation where it concerns the presence of a disamenity. The amenity can be the dimensional area of space, technological and equipment upgrade, accessibility and proximity to social, economic and transport facilities or the exposure to natural landscape providing adequate to excess comfort and well-being opportunities. While a disamenity could be the deficiency or impoverished conditions of the above.

Hence the Residential property values are included as one of the factors in the Environmental Quality Index (EQI). The data is obtained from Osservatorio Del Mercato Immobiliare for the year 2021 for the destination category of Residential use. It is the collaborative outcome of the Osservatorio Del Mercato Immobiliare of the Revenue Agency, Bank of Italy and Tecnoborsa (Chamber of Commerce organization for the development and regulation of the housing sector). The temporality of the data acquisition in quarterly obtained from transcripts of registered sale deeds. While for the evaluation of EQI the R.P.Val. are interpolated to census block unit, for correlation and inter-parameter analysis the zonal polygons indicative of territorial homogeneity of real estate sector is unit of analysis.

Our inquiry commences from the analysis of the spatial distribution of residential property values with respect to the distance from the historic center of Milan, given the strong relevance of the core in the urban planning. Followed by its relationship with the built-up densities (MNDBI), the vegetation cover (NDVI), overall available park areas, population and household densities (PD& HD), illustrating the built and open space interplay of spatial compactness or dispersion. Also, we investigate if energy performance with Energy Efficient Ratings (EER) has any implications on property values as implied by literature studies. Concludingly, if the availability of the number of transit modes as the number of bus and trams stops, highspeed and metro railway stations affect the property values, which would imply significance of transport dependency.

4.2.Remote sensing indicators:

4.2.1.Normalized difference Vegetation Index (NDVI) and Normalized difference Water Index (NDWI):

The most widely anticipated remotely monitored physicality of the environment is its vegetative vitality and cover represented by the Normalized difference Vegetation Index (NDVI) essential in modulating urban micro-climate conditions, human psychological wellbeing and the ecological processes of bio-diversity. While Normalized difference Water Index (NDWI) is significantly indicative of the moisture availability of vegetation. Both these indices are derived from the Sentinel-2 MSI data of the Copernicus Official Open Access Hub (COAH) for the hottest summer day and night average on 2/07/2021. Our foremost inquisition is how the green infrastructure is configured in the urban spatial hierarchy from the central core to the suburban zones. Then, interpretating the relationship of NDVI and NDWI provide insights into land use and land cover dynamics.

4.2.2.Built-up Index:

This analysis of the built environment constitutes two parts. In the first we assess the validity of remotely sensed variables and the formally catalogued variable and their inter- relationship focusing on their accurate predictability of built areas. To do this we compare these variables with derived variable of Percentage Urbanized Areas (PUA) and Percentage Building density (PBD). Both these variables are derived from Database Topografico (DBT 2012) as percentages of urbanized areas and building density as building footprint per census block. Followed by a comparative study on the inter relationship emphasizing built-up indices NDBI and MNDBI with census variable E1 on the number of building and building complexes and the residential built densities of Dusaf 6. In the next we develop various regression models for predicting built-up areas exploring the combinations of different remote sensed variables to achieve utmost accuracy.

Some of these remotely sensed variables include the Normalized difference Vegetation and water Indices (NDVI), (NDWI) and Land Surface Temperature Indices, LST (Summer) and LST (Winter). The temporality of the variables are as follows: the MNDBI, NDBI, NDVI and NDWI were obtained for the summer of 20/07/2021, LST (Summer) 29/07/2021 and the LST (Winter) for the coldest winter day and night averages (14/01/2021). The regression model is built on 60% of the data (3743 data point) and tested on the remaining 40% (1773 data points). The PBD and PUA are the predicted (dependent) variables and the MNDBI, NDBI, NDVI, NDWI, LST(Summer) and LST(Winter) the predictor (independent) variables and six regressions models were developed for each predicted variable with the confidence level of all the models at 95%.

4.2.3.Land Surface Temperature (LST) :

Land surface temperature (LST) is a principal indicator reflecting the extent of land bio-physical changes in the process of surface- atmosphere energy exchanges. It is an integral component of climate change analysis such as urban heat islands and it associated thermal comfortability and mortality causal-interpretative studies. Literature on LST has provided evidences of higher surface temperatures associated with higher urbanization and built densities and lower values attributed to higher vegetative cover. Thus, we inquire what the extent of implication of this phenomenon in Milan is. Also, how is the LST spatial distribution across spatial classes, its relationship with Population and Household densities (PD &HD) and co-relation with NDVI pay a role in distinguishing zones of deficient or impoverished thermal comfort. Hence, LST data reflective of summer hotspots (June, July and August) derived from Landsat 8 Thermal Infrared Sensor (TIRS) processed 5 Meters resolution interpolated at the census block level made available at the geoportale of Commune di Milano is utilized for this study.

4.3.Ecological indicators :

4.3.1.Urban functional diversity (UFD) :

Diversity is analytical function predominately associated with studies pertaining to the biological species distribution. However, since primitive ages concentration of different land-use functions implicitly generate a strong socially knit communities with frequent movement of people and. spatial transparency of the public realm. These attributes render a sense of security through the inherent passive monitoring spatial use functions. These concepts have been reiterated by Jane Jacobs emphasizing concentrated mixed uses, unorganized variations in the built environment as characteristics of socio-spatial vitality.

In more contemporary notions the spatial distribution of land use can be traced in studies that strive to trace the urban rhythm accredited subjective spatio-temporal movement of populations across the urban space for the fulfilment of and accessibility to day-to-life activities and amenities. These rhythms are what renders space dead/ static or alive dynamic depending on the opportunities of social activity that embodies within it. Hence, we analyze the functional diversity of Milan based on the European transport themes of Urban Functional Diversity derivation method. Which delineates nine distinction function residential, schools and universities, sports and recreation, commercial, business (industries, offices, logistics), parks and gardens, residences for the elderly and finally general services (post offices, administration and the like). The presence of utmost number function within a census block is defined as the richness of urban functional diversity which is employed in the EQI, in-place of a spatial unit grid of 1km as the original method suggests. The spatial layers of all these functional uses are obtained from various sources the geoportale Lombardia, opendata of Commune di Milano and Open Street Map (OSM).

The various branches of inquiry include exploring distribution of UFD with respect to the distance from the urban center of Milan assessing the mono-centricity, the relationship of functional diversity with population and household densities (PD&HD) imploring the compactness of agglomerations. Diversity juxtaposition with the build-up densities (MNDBI) and green areas (NDVI) to bring forth insights into spatial ambience of the built vs open interplay. Finally answering the question if higher functional diversity is synonymous to higher residential property valuations.

4.3.2.Building Energy Efficiency Rating (BEER) :

Energy dependance management and transitions is at the core debacle of the climate action resolutions. ENEA the National Agency for New Technology, Energy and sustainable Economic development is an integral part of the National Agency for Energy Efficiency responsible for the introduction of Energy certifications in Italy. Attestato Presatazione Energetica (APE) is the provider that issues the certification on the energy performance in Italy. The certification classes range from G,F,E,D,C,B,A1,A2,A3 and A4 in ascending order of their performance, where G is the least efficiency and A4 the best. It is a legislative mandatory requirement to obtain an APE certification in case of real-estate transactions provided by the seller or letter of the property.

The certifications are based on several characteristics such as the lighting, ventilation, heating and cooling systems, the building envelope and the energy consumption. Higher energy certifications of buildings are assumed to lead to rise in the property value by increasing the construction of energy efficient buildings or energy requalification of buildings and consequently improve the environmental quality with conscious energy use and consumption and guarantying comfortable and healthy domestic environment. The certifications are valid for 10 years and request for requalification is permissible in case of renovations modifying the energy performance. Acknowledging the relevance of energy in assessing the environmental quality and importance of such policy initiatives for this study we inquire the reasons of certification as a proxy to assess the motivation and or challenges of energy transitions, the real-estate type and their comparative emission rate. Subsequently, develop a Building Energy Efficiency Rating (BEER) the numeric counter part of energy performance classes of the issued certifications and analyze its spatial implications.

Building Energy Efficiency Rating (BEER) =

$$\sum_{i=0}^{n} X_{i(1-n)}$$

$$X_{i(1-n)} = \frac{\mathrm{G*1+F*2+E*3+D*4+C*5+B*6 +A4*7+A3*8+A2*9+A1*10}}{\text{Total no.of registercd Building certifications in the i}^{th}\text{ Census block}}$$

Where, $X_{i(1-n)}$- is the census block

The assigned weights are based of the relative assigned ranking values corresponding to the scale of the categorical certifications.

The data set we analyzed is (APE) practice database for the Lombardy region available on the open data Lombardia platform updated weekly. The database used composed of issued certifications from 2015-August 2021. A generic hypothesis is that the older and poorly maintained the buildings are the harder it would be to achieve better energy efficiency. To further enquire if the energy efficiency performance was based on the state of conservation of buildings, we derive a state of conservation index from aggregating the number of buildings in different states of conservation. We obtained the data from ISTAT 2011 and calculated the index as follows: E28- Residential buildings with excellent state of conservation, E29- Residential buildings with a good state of conservation, E30- Residential buildings with a poor state of conservation, E31- Residential buildings with a very poor state of conservation.

The Agg. state of conservation of buildings for i^{th} block = $\frac{\mathrm{4*E28 +3*E29 +2*E30 +1*E31}}{\text{Total no.of buildings in each conservational state(E28+E29+E30+E31)}}$

While, the inference as to the age of the buildings was evaluated from the notes of the (APE) certifications.

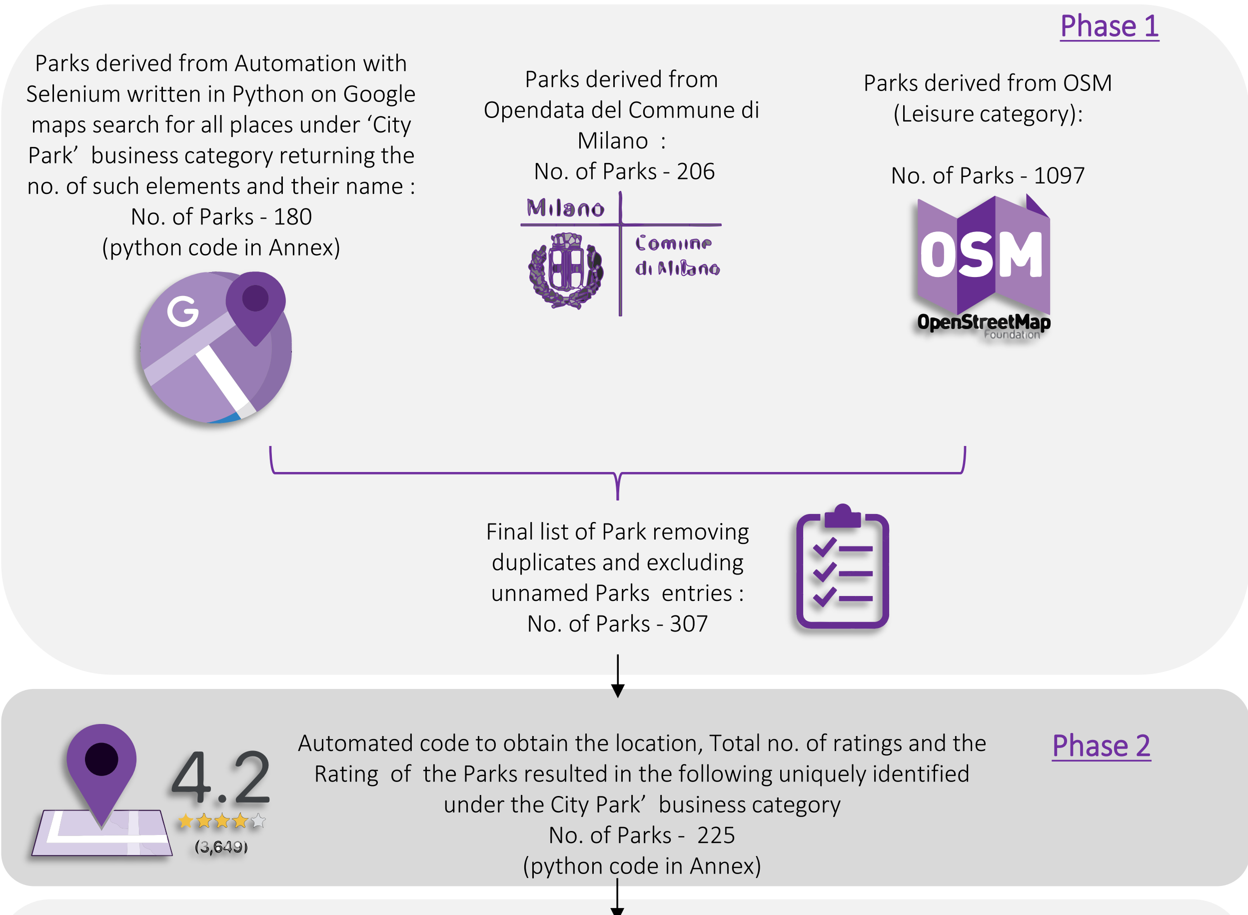
4.3.3.Quantifying the quality of parks and garden of Milan throug the perceived satisfaction:

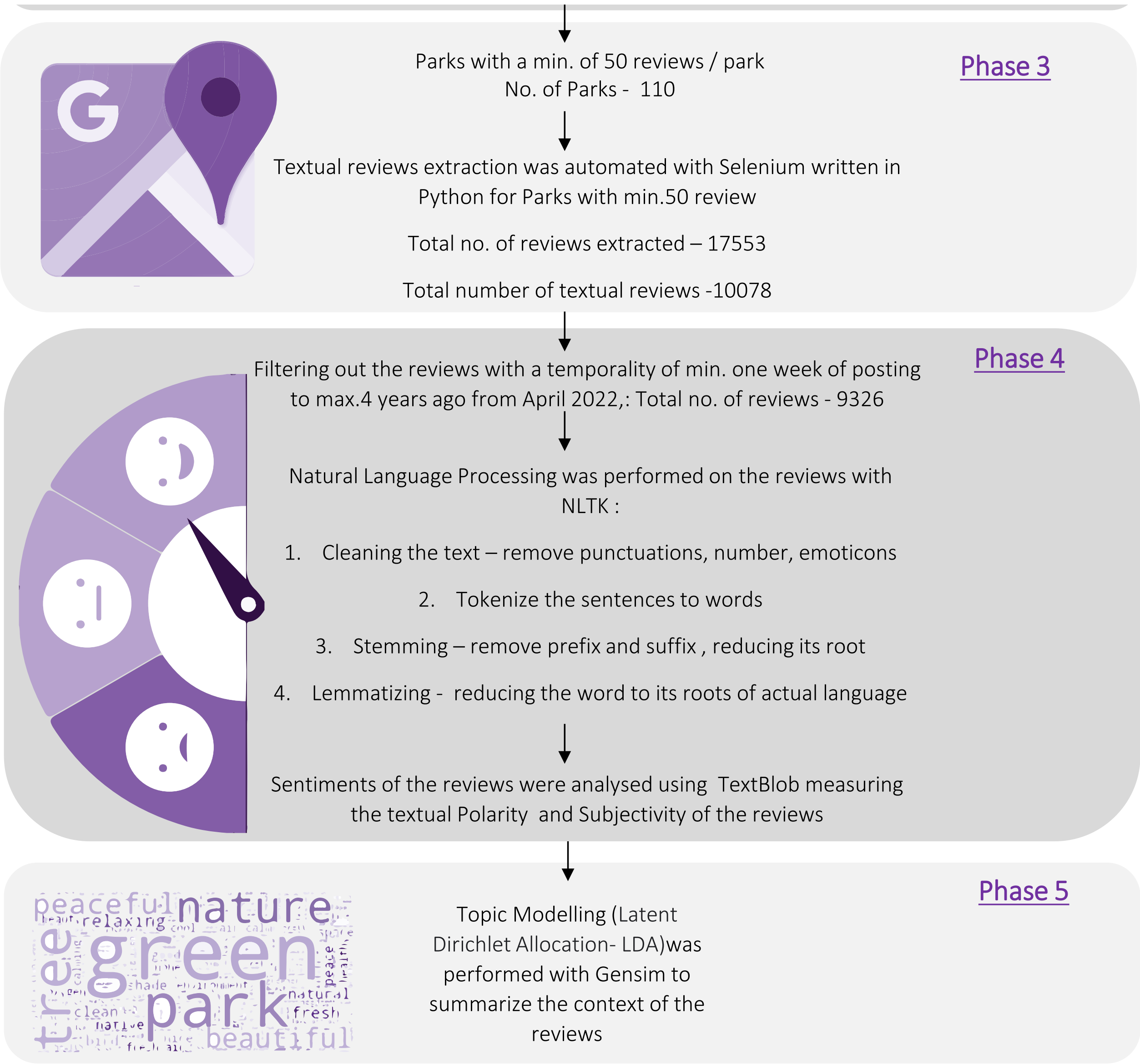
Language is a structured system developed and evolved by human beings as means of communication whose form can either be speech, written text or symbols. In the digital age of world -wide- web communication, social median acts as a podium for setting forth individual views and opinions. Where the platform of Google Maps services is foremost a navigational application that composes tools which categorically classifies the destination locations according to their functional use for more nuanced geospatial search and directional assistance. Provided with functions to elaborate the destination details along with social interface comprising prompts and tools to acquire and evaluate the perceived satisfaction levels and experiential feedback associated with the functioning performance of the destinations.

The Google Map reviews section comprises a numeric five-point star rating and textual reviews as summarization of the user's online posts on the platform. These user-generated rating and textual reviews influence the destination decisions of other users either encouraging or discouraging visitation. Thus, extensively employed in the private sectoral managerial studies is the utilization of this data to render insights into the quality or performance associated satisfaction of products, goods and services attainable at these destinations. Building on these, we analyze the perception of users of the public parks and gardens through their reviews on the Google map review platform. As literature widely encompassed the significance of public green infrastructure particularly parks and gardens. Hence, inquisition into its performance and its contiguous relevance to expectations of the urban society becomes imperative. Fig.8. gives a brief description of this process.

From the literary application of studies employing social media data, our analysis attempts to exploit its potential in understanding the qualitative aspect of user behaviors and expectation of the public greens of Milan and use it as variable in

Fig.8.Workflow of Sentiment analysis of Parks and Gardens in Milan :





the assessment of the overall environmental quality of Milan as an EQ index. Simply put, it is the use of public assessments as a method of urban public parks and playgrounds appraisal. Where perceived functional and aesthetic quality of parks and gardens from the reviews of visitors on the geo-browser Google Maps are quantized. To do this we employ Selenium as the webs-crapper, NLTK as text pre-processor, TextBlob as sentiment analyzer and finally Gensim as the topic modeler of reviews using python programming.

The analysis is composed of five phases. Foremost, in phase 1 the parks and gardens within the metropolitan city of Milan is enlisted from various data sources like the municipal open-data website, OSM (Open Street Map) and preliminary Google map search of location within the 'city park' category. Comparatively assessing and filtering out named entities of public parks and gardens with spatially unique relevance we arrive at a final list of 307 parks and gardens for which detailed data extraction is carried out. In the second phase the Total no. of reviews attained by each park and garden and its overall rating are extracted using Python Selenium. Here we observe the number of parks and garden returned is reduced to 225 nos. as some of them are not available on google maps platform. Among the parks and gardens extracted we filter those with at least 50 reviews including textual and star ratings, which leave us with 110 parks and gardens for which the textual reviews are extracted in phase 3. From the reviews extracted it can be noted that a substantial number of the reviews are non-textual. Thus, is phase 4 from 10078 reviews we filter out 9326 reviews, only those that were posted utmost four years ago from the date of extraction February 2022.

These reviews are then subjected to Natural Language Processing (NLP) which breaks up the sentence composition of the reviews to the most relevant words. Sentiment is an attitude, a thought prompted by feeling. Considering attitude or thought stems from a way of thinking or point of view which can either be personal, individualistic, subjective or impersonal, unbiased, objective. Whereas emotion or mental state of feeling, happiness, sadness, fear, adoration, awe, contempt is embedded in the positive to negative emotional spectrum.

These two attributes of sentiments, the inclination of subjectivity and emotional polarity is quantified from textual data by analyzing the polarity and subjectivity categorization using TextBlob in python. While the sentiment function of TextBlob library assigns a polarity score for each word among the value range of -1 to +1 left to right from the most negative to the most positive. Which is then subsequently used to derive the overall polarity of each sentence and thus each review. Consequently, sentimental polarity score of all the reviews is calculated. To comparatively analyze the overall perception of parks and gardens as attributed from the polarity score of their reviews, we utilize the median of the polarity score. The median values which are reflective of the 50th percentile of the reviews would give clarity as to the most predominant sentiment along polarity spectrum, as perceived and communicated by visitors in their reviews. Subsequently the subjectivity score of the reviews and its comparative affiliation to the median of parks and garden review is derived similarly but along the value range of 0 to 1, where '1' would imply the reviews are highly personal or subjective and '0' impersonal or factually objective.

To further accentuate the context which generates the sentiments encapsulated in the text of the reviews we perform topic modelling using Gensim. Conceptually the reviews are considered as unstructured words, which are counted and grouped according to their similarity of occurrence within patterns which infer relationship with one or more topic clusters. The soundness of this is calculated according to the perplexity function which a coherence scoring of the word clustered according to topics. Or for simplicity from the graphical visualization of the topic cluster the more apart and non-overlapping the clusters are the better the topic modeled from the textual data. The Table 1. briefly illustrates the indicators, their sources and its means of derivations.

Table.2.Indicators, Datasources and calculation methods :

S. No.	Indicators	Calculation	Data Source
1.	Population Density (PD)	Population (P1- Total Resident population persons)/ Area (of the census unit m2)	Instituto Nazionale di Statistica (ISTAT)- CEZ 2011
2.	Housing Density (HD)	Housing units (PF1-Total Residential Households)/ Area (of the census unit m2)	Instituto Nazionale di Statistica (ISTAT)- CEZ 2011
3.	Normalized Difference Vegetation Index (NDVI)	(NIR-RED) / (NIR+RED) Sentinel bands: (B8- B4) / (B8 + B4)	Sentinel-2 MSI data from Copernicus Official Open Access Hub (COAH) D.t. Day and Night average for summer of 2/07/2021
4.	Normalized Difference Water Index (NDWI)	(GREEN-NIR) / (GREEN+NIR) Sentinel bands: (B3 – B8) / (B3 + B8)	Sentinel-2 MSI data from Copernicus Official Open Access Hub (COAH) D.t. Day and Night average for summer of 2/07/2021
5.	Normalized Difference Built-up Index (NDBI)	(SWIR-NIR) / (MIR-NIR) Sentinel bands: (B11 – B8) / (B11 + B8)	Sentinel-2 MSI data from Copernicus Official Open Access Hub (COAH) D.t. Day and Night average for summer of 2/07/2021
6.	Land Surface Temperature (LST)	in ^{0}C	Summertime hotspots derived from Landsat 8 Thermal satellite from geoportale Commune di Milano
7.	Building EnergyEfficiency Rating (BEER)	G,F,E,D,C,B,A1,A2,A3,A4 (Highest to the lowest classes of energy efficiency) Building Energy Efficiency Rating= $\sum^{n}_{i=0} X_{i(1-n)}$ $X_{i(1-n)} = \frac{G*1+F*2+E*3+D*4+C*5+B*6+A4*7+A3*8+A2*9+A1*10}{\text{Total no. of registered Building certifications in the } i^{th} \text{ Census block}}$ $X_{i(1-n)}$ – is the census block The assigned weights are based of the relative assigned ranking values corresponding to the scale of the categorical certifications.	Attestati di Prestazione Energetica (APE), bulding energy certification registry on Dati Commune di Milano(Open data Milano) for (2015-2021)

8.	Urban Functionality Diversity (UFD) ∀ indicator is derived from EU transport theme	$\sum_{ij} Pop_{ij}$ ($Pres_{ij} > 0$) Pop_{ij}– Fraction of population in the urban area in zone 'i' [fraction] $Pres_{ij}$-Presence of functions 'j' in zone 'i' [Binary unit] The nine predefined functions: Business (Industry, offices, Logistics, etc.) Hospitals and Medical Services General services (post, administration, etc.) Schools Commercial (Shops, supermarkets) Sports and recreation Residential Residence for elderly people Parks and green all the functions aggregated onto the Census block group instead of a spatial unit grid of 1km as the original framework suggests. The overall UFD score of Milan is ontained from the above formula, while for the EQI only the presence of diversity rank is utilized.	Geoportale Lombardia, Dati Lombardia (Lombardy Open data) and Open Street Map (OSM)
9.	Residential Property Value (R.P.Val.)	In Euros / sq. m.	Osservatorio del Mercato Immobiliare (OMI) of the Agenzia delle Entrate.
10.	Sentiment analysis of Urban Public Green Space	Sentiment of each review is calculated as its polarity inclination and the output result is the overall degree of polarity ranging from -1 ________ to ________ +1 negative positive Polarity score-is the aggregated polarity score of each Park and Garden is obtained as the median polarity score i.e. the polarity of the 50^{th} percentile of the reviews. The rank of the sentiments = Polarity score * D_Z Where, D_Z=The normalized value of inversed distance from the respective park and garden	Google map reviews extracted with python Selenium, Natural Language Processing (NLP) done with NLTK (Natural Language toolkit) and sentimental analysis with Text blob a Rule based sentiment classification.

4.4.Method of Aggregating the Indicators:

This study is based on GIS approach for interpretating and evaluating the environmental quality. The reference unit of analysis is the census block group where each parametric indicator is interpolated to this unit as the represented average of values corresponding to indicators, as distributed within each block. The Fig. 9. summarizes the overall workflow. Considering the values that the indicators would take can be either continuous or discrete, the process of aggregating the EQI is slightly different. Generally quantitative parametric indicators assume continuous values which would include the PD, HD, NDVI, NDWI, MNDBI LST and R.P.Val.

While, qualitative parametric indicator would assume discrete values composing the UFD, EER and the sentimental score of the parks and garden reviews The indicators with continuous data values of each block unit is primarily normalized with the mean and standard deviation values among itself. This is followed by assigning the rank as a five-point valuation with values from 1 to 5 among the value range of each indicator, the lowest rank reflects the lowest values and the highest vice versa.

The rank of each indicator is then calculated employing the difference of value of each block unit and maximum value of the range accompanied with the maximum possible valuation of rank which is 5 along with a rank normalization factor (1-5)/(1-5) the difference of the highest and lowest rank. As in case of indicators with discrete values the normalization step is skipped and weighted as requisite of each indicator, this is then followed by the ranking method. The overall EQI is aggregated by summing the parametric indicators whose preliminary analysis reflect to contribute positively to the environment and those that infer depreciating environmental attributes are summed negatively.

Fig.9.Indicators Aggregation Workflow:

Continuous variable

1. Population Density (PD)
2. Housing Density (HD)
3. Residential Property value values (R. Val)
4. Land surface Temperature (LST)
5. Normalized Difference Vegetation Index (NDVI)
6. Normalized Difference Water Index (NDWI)
7. Modified Normalized Difference Built-up Index (MNDBI)

Normalized using statistical method of Z-Score:

$Z = (X_i - \mu_i)/\sigma_i$

where,

X_i- Observation value in the GIS polygon
i- is the parameter
μ_i- Mean value of the parameter
σ_i- Standard deviation (Std.Dev.) of the parameter

Discrete variable

8. Social media sentimental analysis of Urban green spaces
9. Urban Functional Diversity (UFD)
10. Building Energy Efficiency Rating (BEER)

All the values of each parameter are ranked by linear interpolation:

$Rank = [(Obs - Obs_{max})*(Rank_{min} - Rank_{max})/(Rank_{min} - Rank_{max})] + Rank_{max}$

Where,

$Obs -$ observed z-core value
$Obs_{max} -$ Max. z-score value
$Rank_{min} -$ Min. rank assigned (1)
$Rank_{max} -$ Max. rank assigned (5)

UEQI values = $\sum_1^n Rank_i$, The values of variable that contribute inversely to UEQ (PD,HD,LST,MNDBI) reversely summed.

5.ANALYSIS AND INFERENCES

5.1.Population Density (P.D.)

5.2.Household Density (H.D.)

5.3.Analyzing the demand trends of the Housing stock with respect to the population growth (Regression analysis of Population and Housing Densities)

5.4.Normalized Difference Vegetation Index (NDVI)

5.5.Normalized Difference Water Index (NDWI)

5.6.Assessing the validity of different indicators to identify the Built environment

5.7.Land Surface Temperature (LST)

5.8.Building Energy Certification Class

5.9.Urban Functionality Diversity (UFD

5.10.Residential Property Value (R.P.Val.)

5.11.Sentiment analysis of Urban Public Greens

5.12.Environment Quality Index (EQI)- tracing the zones of preliminary intervention

5.13.Potentials and Limitations of the framework

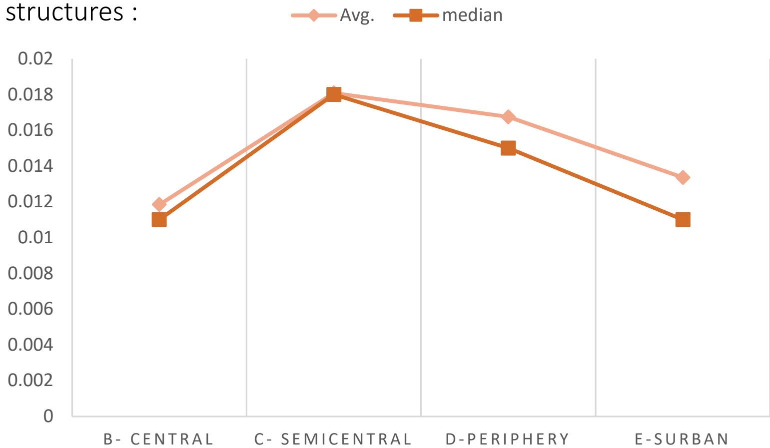
5.1.Population Density (P.D) :

6.1. Population Density (P.D) :

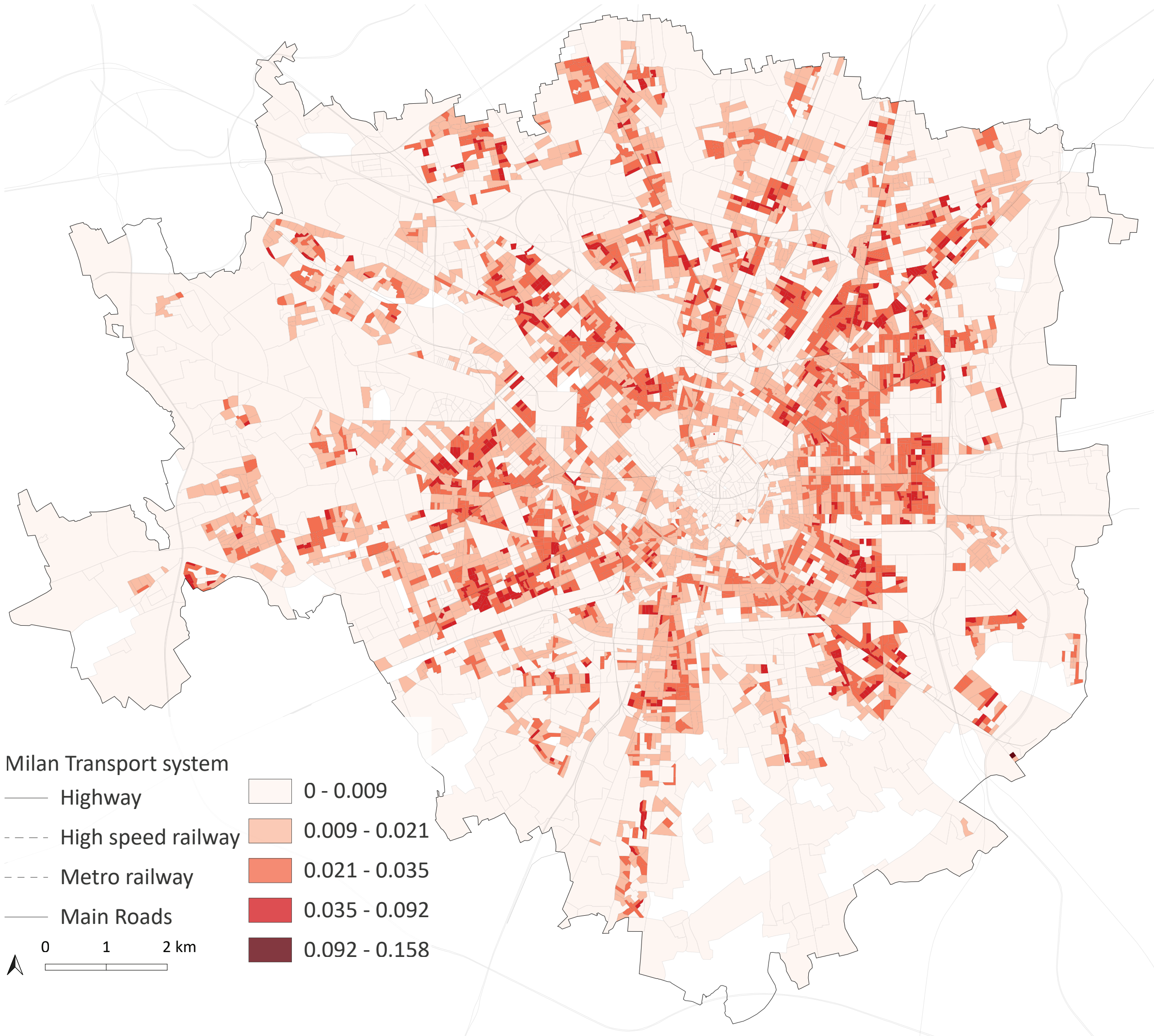
Map.0.1. Illustrates the spatial distribution of Population Densities (PD) and Fig.10. demonstrates the average and median density distribution across various spatial classifications. Milan is monocentric with the historic center as the core of business and commerce. Hence, it is here in the central and the suburban spatial classification where both Population and Household Densities (PD and HD) are the least observing both the average and median density values. The highest population and household densities are found in the semi-central area followed by the peripheral areas. The difference in the average and median density values of PD in the central and semi-central areas is insignificant, reflecting a homogenous spatial saturation of densities in these regions. In case of PD in the suburban and peripheral areas there is higher difference in their average and median values depicting a heterogenous spatial distribution of density.

Analyzing density distribution with respect to the linear proximity to bus and tram stops exhibited a weak negative correlation r=-0.24 and In case of the metro and stations highspeed both at r=-0.13 also a weak negative relation. As the correlations are weak, we could infer that in Milan the spatial agglomerations do not concentrate around the transit hubs.

Fig.10.Population Density destribution across the urban spatial structures :

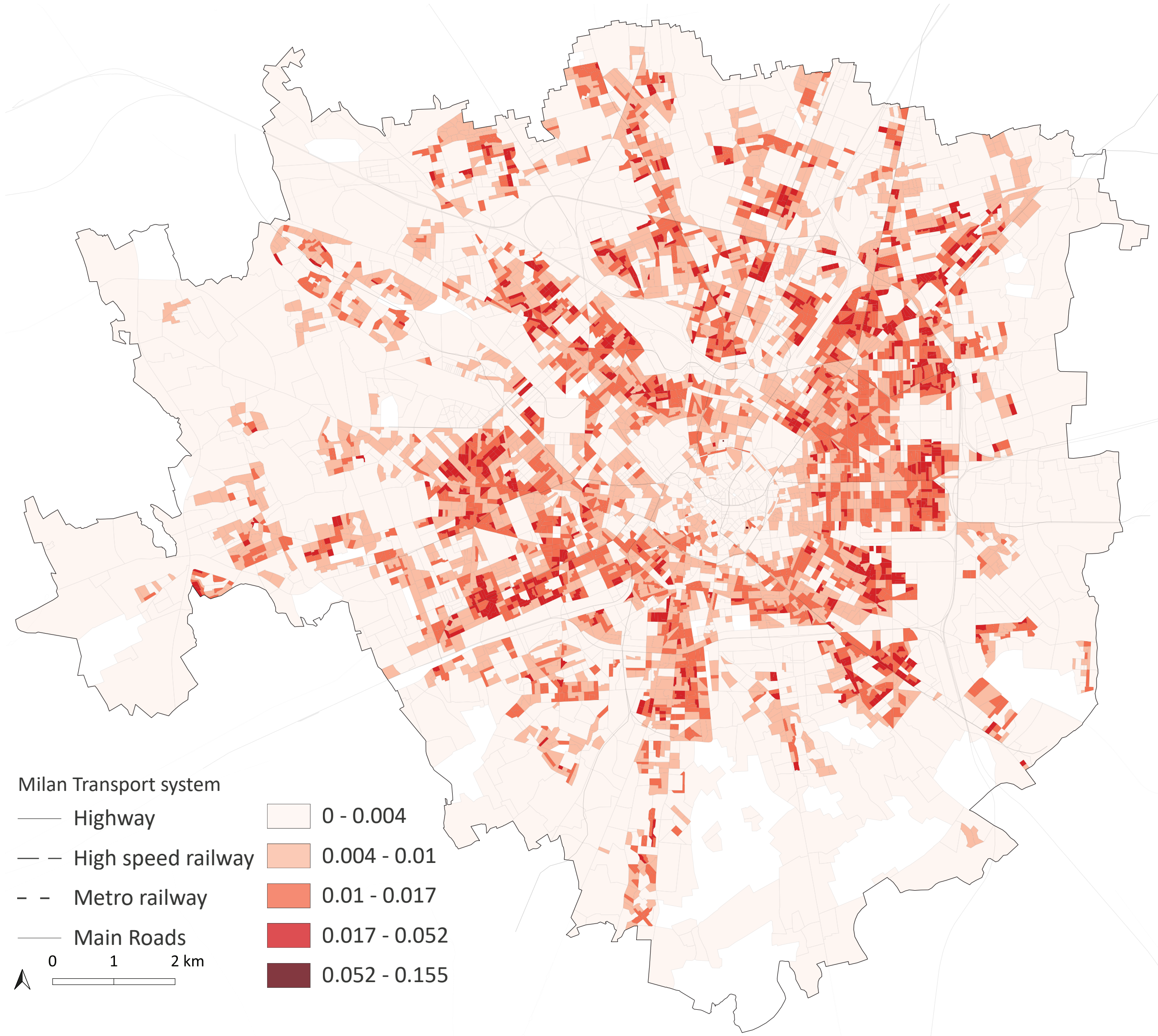


Map.01 .Population Density = (P1- Total Resident population persons)/ Area (of the census unit m^2) :



5.2.Household Density (H.D.) :

Map.02 .Housing units (PF1-Total Residential Households)/ Area (of the census unit m²) :



In Map.02. We can observe the spatial distribution of Household Densities (HD) and Fig.11. supplements the analysis of HD across spatial classes with respect to averge and median distribution central tendencies of the HD values. The HD values follow similar spatial relation of PD, where household densities are high in the semi-central and peripheral areas and low in the central and suburban areas. The difference in the average and median HD values like in PD follow somewhat similar trend with higher difference in the peripheral and suburban areas. However, the difference is also observable in the central area.

The HD correlation with respect to the proximity to transit stops is similar to the PD. The HD correlate with proximity to bus and tram stops at r=-0.24, with metro and highspeed railway stops both at r=- 0.16 respectively exhibiting weak negative correlations. Thus, having insignificant conclusions of spatial relationship between household densities and proximity to transit. However, population and household densities generally have a strong correlation, as the city economically expands, the housing stock requirements increases to accommodate the incoming and expanding populations. The PD and HD values are reflective of this growth cycle correlating at r= 0.97, a strong and positive interdependence.

Fig.11.Household Density across the urban spatial structures :

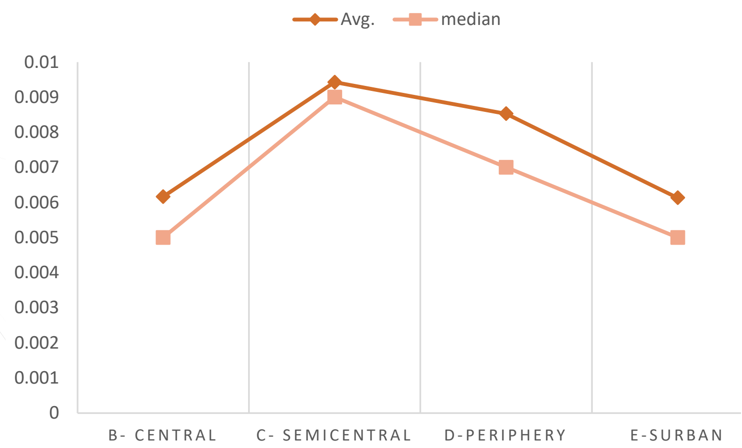


Table.3.Regressions analysis of Population Density and Household Density :

Model:	Model 0							
Dependent Variable:	HD							
Independent Variables:	PD							
Equation:	HD =-0.000632 + 0.538*PD							
Regression Statistics: Model 0 for HD (1 variable, n=4367)								
	R-Squared	Adj.R-Sqr.	Std.Err.Reg.	Std.Dep. Var.	# Fitted	# Missing	Critical t	Confi-dence
	0.923	0.923	0.002	0.007	4367	0	1.961	95.0%
Coefficient Estimates: Model 0 for HD (1 variable, n=4367)								
Variable	Coefficient	Std.Err.	t-Statistic	P-value	Lower95%	Upper95%	VIF	Std. Coeff.
Constant	-0.001	0.000	-12.565	0.000	-0.001	-0.001	0.000	0.000
Pop.Densit	0.538	0.002	228.397	0.000	0.533	0.543	1.000	0.961
Analysis of Variance: Model 0 for HD (1 variable, n=4367)								
Source	Deg. Free-dom	Sum Squares	Mean Square	F-Statistic	P-value			
Regression	1	0.223	0.223	52165.364	0.000			
Residual	4365	0.019	4.268E-6					
Total	4366	0.241						

5.3.Analyzing the demand trends of the Housing stock with respect to the population growth (Regression analysis of Population and Housing Densities) :

The two variables PD and HD have a strong positive correlation about r=0.97, hence further regression analysis to infer their statistical linear relationship summarized in the following linear regression model in Table.3. Thus, Elaborates the mathematical linear relationship of the values of the both the variables, in-terms of how variation in Housing density assuming it as the predicted/dependent variable can be explained with population density as the predictor/independent variable. Both variables' data are split into training and testing dataset composed of 70% and 30% of the datasets respectively, and the regression model is built on training dataset the results of regression are summarized in the Table. 2. While, Fig.12. highlights points of discrepancies in the linear trends and Fig.13. locates their geographic space.

The simple regression model has a confidence of 95% and the p-value<0.001 hence the null hypothesis of a zero correlation of the predictor variable is rejected. The R2 value explains the goodness of fit of the model for the training dataset 92% (0.923) and the testing dataset 95% (0.95188) reflecting that the model captures 92 - 95% the variation of Housing densities explained in terms of the Population density variable. Also, the Root Mean Square Error (RMSE - square of the residual errors) of the model on the testing dataset is 0.01 as the RMSE value is closest to 0 the model's accuracy is very high. The statistical linear relation of PD and HD highlights three data point, the census blocks where household densities are more in provision than the population inhabitation Fig.12 and 13. The building typology there may be low raised individual building or villas.

Fig.12.Regression Model 1 for HD (1 variable, n= 4367)
HD =-0.000632 + 0.538* PD

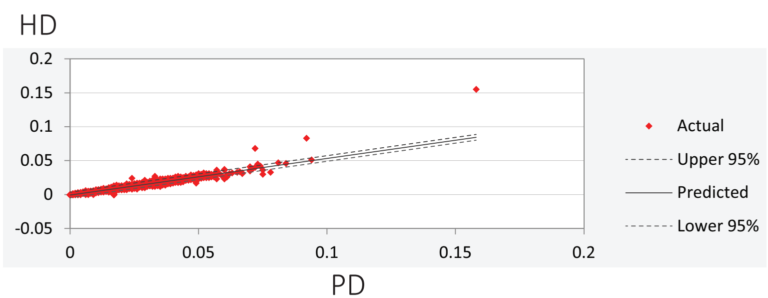
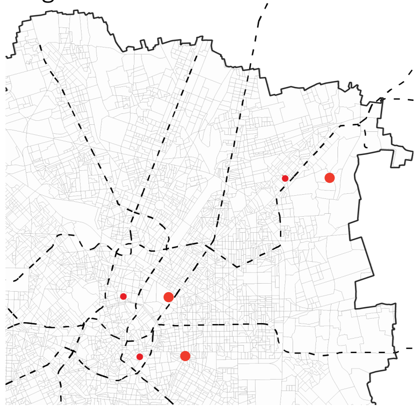


Fig.13.PD and HD outliers :



5.4.Normalized Difference Vegetation Index (NDVI) :

Map.03 .Normalized Difference Vegetation Index (NDVI) :

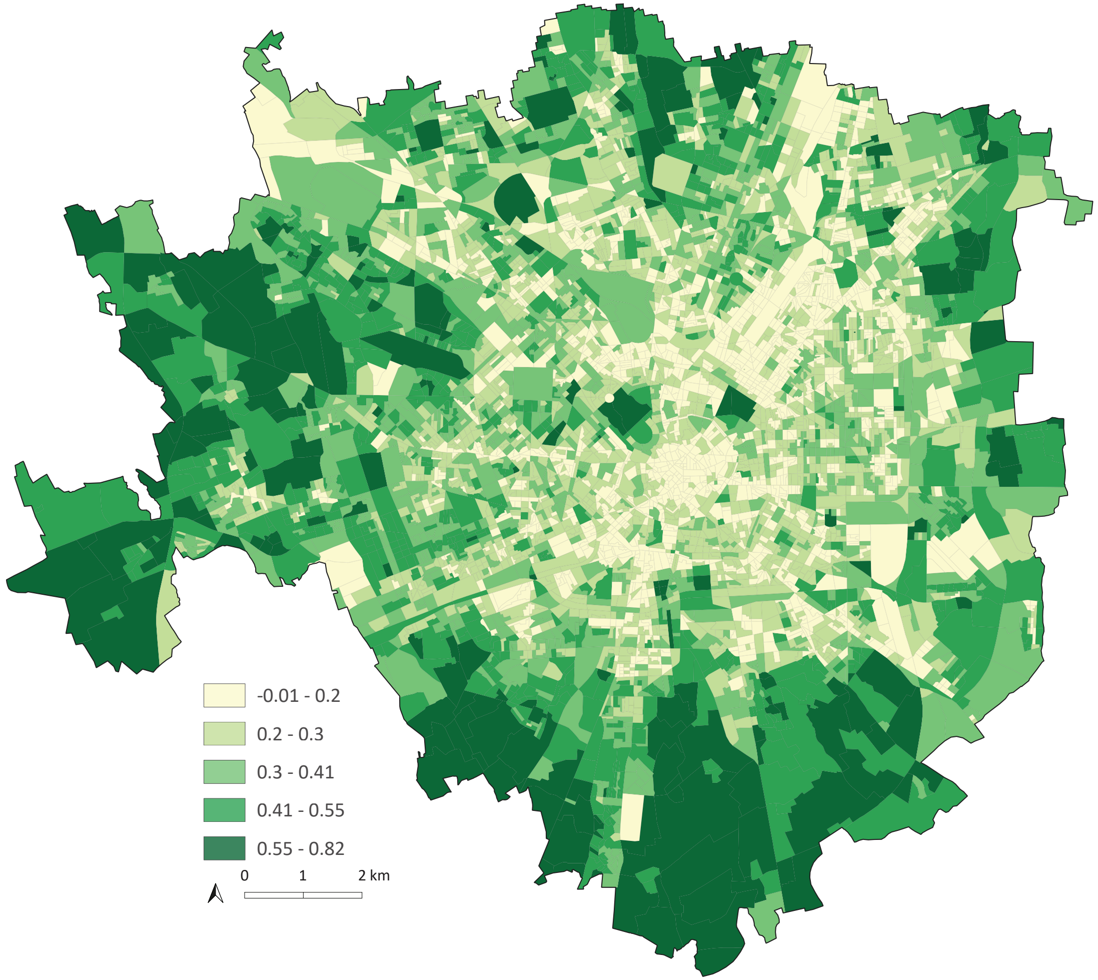
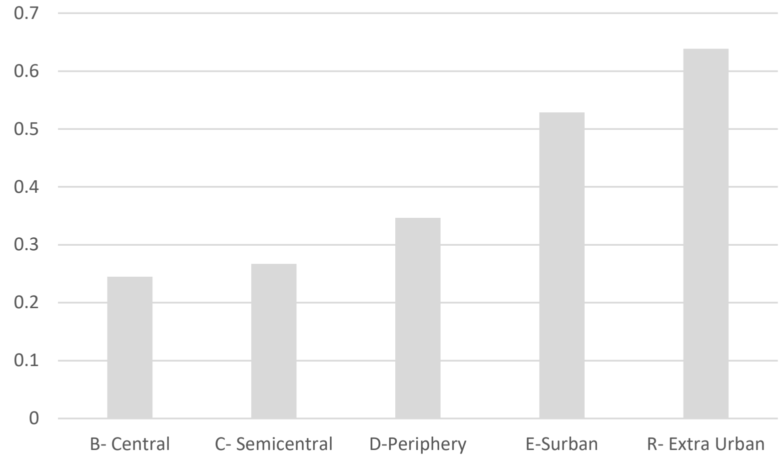


Fig.14.NDVI distribution across urban spatial structures :



Map.03. Demonstrate the average NDVI observations within each census block therein indicative of vegetative presence, while Fig. 14. Illustrates the trend of vegetation NDVI distribution spatially across the spatial classes. The NDVI values less than 0.1 indicate areas of barren rocks, sand or snow, values between 0.2 - 0.5 indicate sparse vegetation, the shrubs and grasslands and values greater than 0.6 to 1 indicate dense vegetation, tropical forests or peak growth of crops. The PD and HD have a weak negative correlation with NDVI values respectively at r=-0.29 and r=-0.31, exhibiting scenario where higher vegetation density the lower the Population and Household densities. This is further reflective in the NDVI distribution across the spatial hierarchy, where the central urban area has the least values and the sub-urban and extra-urban the highest values. Investigating the relation of NDVI with the proximity to transport hubs (the bus and tram stops, metro and Highspeed railway stations) exhibit weak positive correlations, i.e.as the distance to a transport hub increases, the quality of vegetative land cover decreases. The correlation values are as follows r=0.35 with proximity to a bus or tram stop, r= 0.37 with proximity to a metro stop and r=0.41 the proximity to a highspeed railway stop. The strongest positive correlation of NDVI is with NDWI at r=0.93 and the strongest negative correlation is with MNDBI at r=-0.95. The correlation between NDVI and NDWI infer that higher the vegetation higher is the surface water or soil moisture content. And with MNDBI an inverse trend where higher the built area the less is the green landscape cover.

5.5.Normalized Difference Water Index (NDWI) :

Presented in Map.04. is the census block averages of NDWI observations and Fig.15. demonstrates the relations between NDWI and NDVI in its value attributes of landcover classifications. The NDWI values between 0.2 – 1 represent surface water, 0.0 – 0.2-indicates flooding or humid areas, -0.3 – 0.0-indicates moderate drought or non-aqueous surface, -1--0.3-indicate drought or non-aqueous surfaces. The NDWI values correlate similar to NDVI, however the correlations values are numerically higher than NDVI. The PD and HD values have relatively strong positive correlation with NDWI at r= -0.38 and r=-0.40 respectively. Assessing the correlation to proximity to nearest transport hub and NDWI also have relatively strong positive correlation with the bus and tram strop r= 0.36, the metro and highspeed railway stations respectively at r= 0.38 and r=0.42. And most significantly with MNDBI the correlation is a strong negative r= -0.99.

Map.04 .Normalized Difference Water Index (NDWI) :

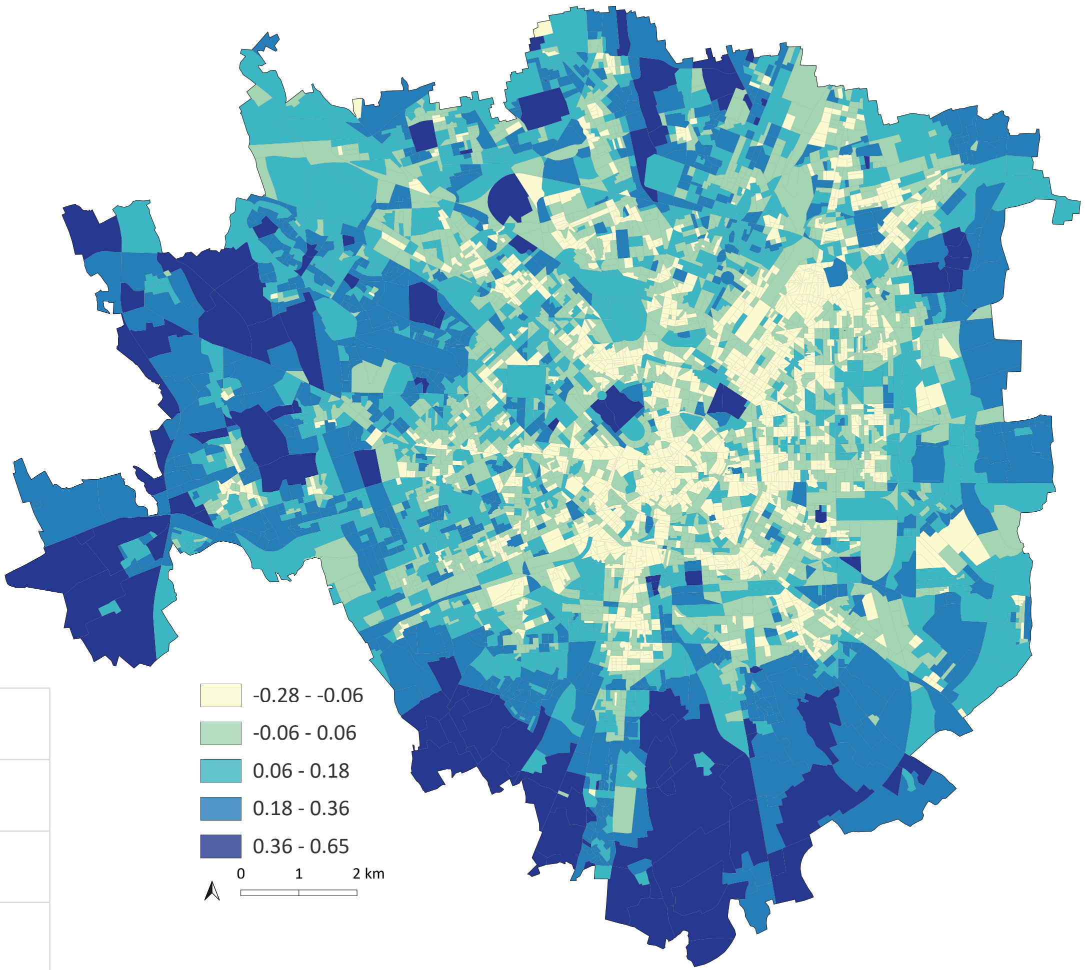
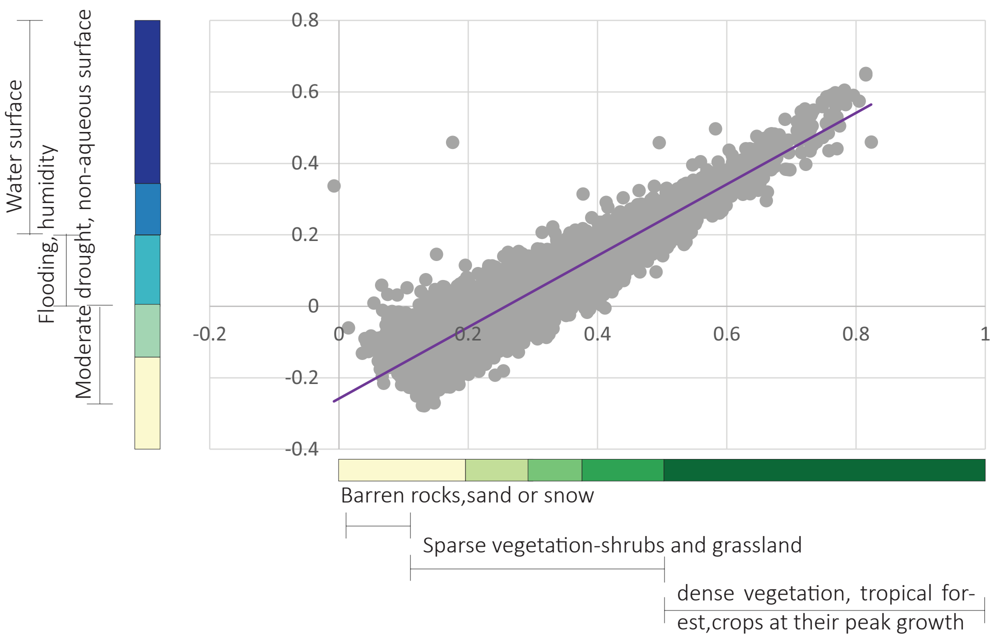


Fig.15.NDVI and NDWI relationship charecteristics :



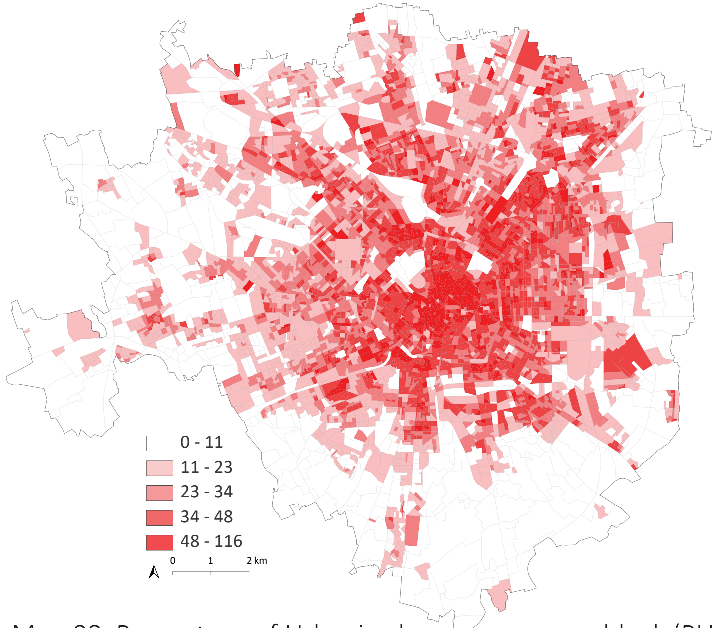
Further analyzed is the bio-physical comparison of NDVI and NDWI classification of territorial land cover in Fig.14. in which the NDWI value classification of moderate drought or non-aqueous areas in association to the NDVI classification represents the juxtaposed built and open urban landscape. Where the urbanized areas are composed of nonaqueous surface and predominantly sparce vegetative cover. The parks gardens and agricultural areas have a varied range of sparse to dense vegetative cover with relatively high surface water or moisture availability.

5.6.Assessing the validity of different indicators to identify the Built environment :

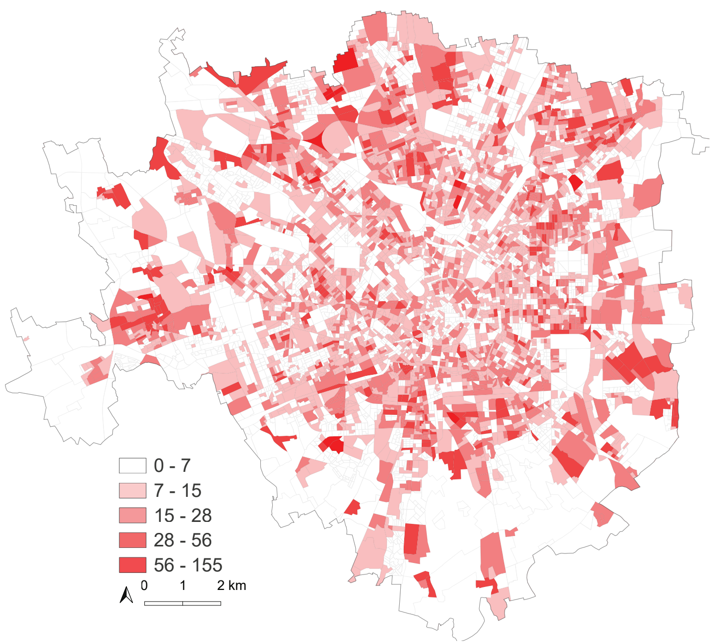
This section analyzes the prospects of DUSAF derived densites Map.05., no. of buildings and building complexes from ISTAT Map.06.and remotely sensed built up indices Normalized Difference Built-up Index (NDBI)Map.09. and Modified Normalized Difference Built-up Index (MNDBI) Map.10. in accurately identifying built-up areas. The base point of analyzing this is through two variables derived from DBT 2012 one the Percentage of urbanized area (PUA) Map.08. and the other Percentage Building Density (PBD) Map.07 indicating the extent of urbanization and building footprint occupancy within each census block group.

Map.05 . Residential densities (Dusaf 6)

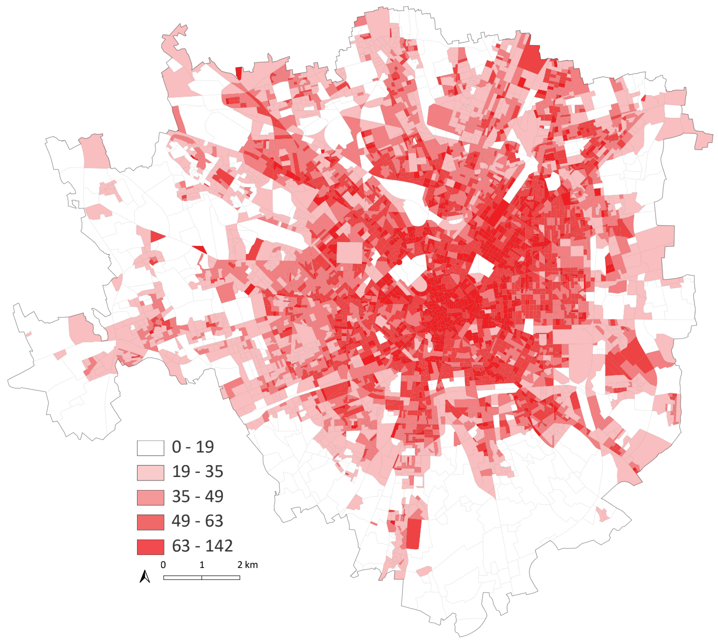
Map.07 .Percentage of Building Density per census block(PBD):



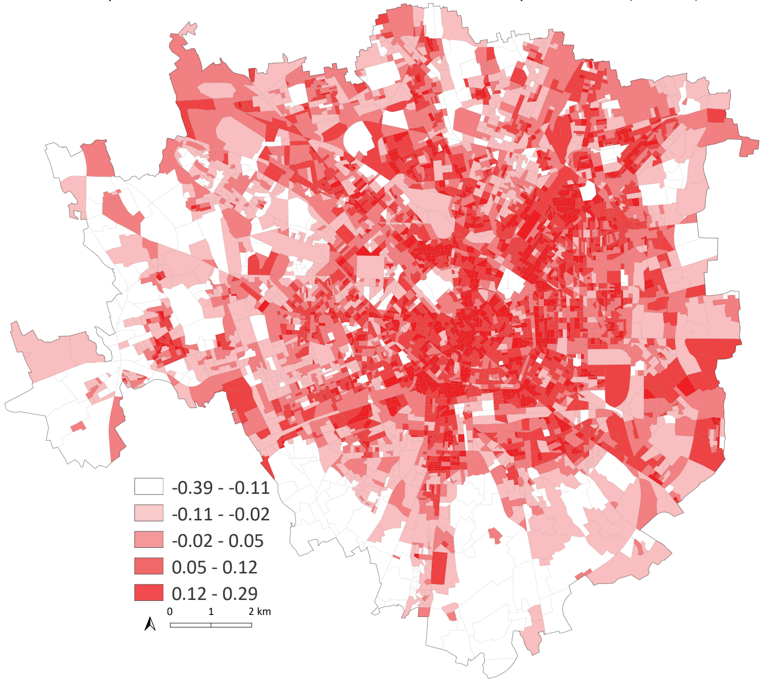
Map.06 .Total no. of Buildings and building complexes (E1-ISTAT 2011)



Map.08 .Percentage of Urbanized area per census block (PUA) :



Map.09 .Normalized Difference Built-up Indeex (NDBI) :



Map.10 .Modified Normalized Built-up Index (MNDBI) :

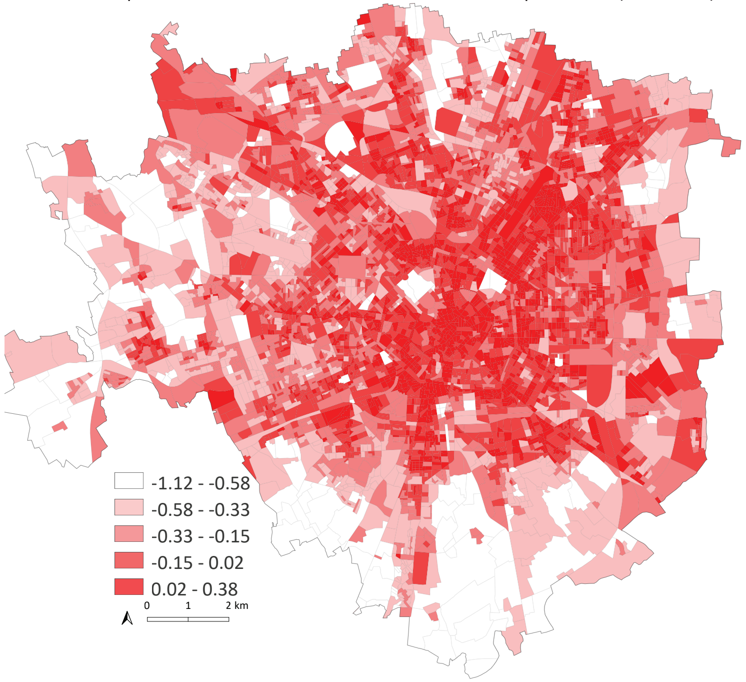


Table.4.Correlation matrix of variables identifying interdependencies:

	NDBI	MNDBI	LST(Summer)	**LST(Winter)**	NDVI	NDWI	Dusaf 6	Census- IT E1
NDBI	1	**0.99**	0.49	0.42	-0.91	-0.99	0.43	0.17
MNDBI	**0.99**	1	0.52	0.44	-0.96	-0.99	0.46	0.17
LST(Summer)	0.49	0.52	1	0.62	-0.52	-0.54	0.53	0.07
LST(Winter)	0.42	0.44	0.62	1	-0.43	-0.46	0.36	-0.01
NDVI	-0.91	-0.96	-0.52	-0.43	1	0.93	-0.47	-0.15
NDWI	-0.99	-0.99	-0.54	-0.46	0.93	1	-0.46	-0.18
Dusaf 6	0.43	0.46	0.53	0.36	-0.47	-0.46	1	0.12
Census-IT E1	0.17	0.17	0.07	-0.01	-0.15	-0.18	0.12	1
PBD	**0.79**	**0.81**	**0.55**	**0.50**	**-0.77**	**-0.82**	0.48	0.22
PUD	**0.71**	**0.74**	**0.60**	**0.54**	**-0.74**	**-0.75**	0.47	0.04

Map.09 and Map.10. Represents the NDBI and MNDBI spatial distribution of census block averages. Table.4. Analysis the correlation between all the indicators of built-up, vegetation and surface temperature derived only for the hottest and coldest day. The inference from this analysis is as follows. The variables MNDBI, NDBI, NDWI AND NDVI have higher correlations with Percentage Building Density (PBD) than with Percentage Urbanized Areas(PUA).

Where from the correlation matrix Table.4 we observe that the built-up indices MNDBI and NDBI obtain the strongest positive correlation r=0.81 and 0.79 respectively with PBD and r= 0.74 and r=0.71 respectively with PUA. While the NDWI and NDVI obtain the strongest negative correlation r=-0.82 and r=-0.77 respectively with PBD and r=-0.75 and r=-0.74 respectively with PUA. The surface temperatures however have a higher correlation with the PUA than with PBD. The LST (Summer) and LST(Winter) have a moderately strong positive correlation r=0.55 and r=0.50 respectively with PBD and r=0.60 and r=0.54 respectively with PUA. While residential density classification of Dusaf6 exhibits a relatively strong positive correlations r=0.48 with PBD and r= 0.47 with PUA, the census variable E1 conclusively has no significant correlations with either variable.

Based on the correlation analysis we inquire regression models composed of primarily NDBI ,MNDBI along with other contributing indicators to check for the most accurate identification of the Percentage Urbanized Areas (PUA). The details of the modelling are summarized in Table.5.

The R value of simple linear regressions modelling representing the goodness of fit of the model developed with individual variables MNDBI and NDBI in predicting PUA is around R=0.48 to 0.51 and R=0.53 to 0.56 respectively approximately considering the evaluation of both the training and the test data results. The further Multiple Linear Regressions (MLR) modelling of PUA with NDBI as the significant predictor and LST(Summer) and LST(Winter) as the less significant variables increases the goodness of fit up-to adjusted R2= 0.61(Table.5. Model 5). But, the contribution of the less significant variables in the models, the LST(Summer) and LST(Winter) either individually and together improve the adjusted R2 by only 0.01 to 0.002 roughly 2% (Table.5. Models3-).

However, the MLR model with MNDBI as the significant predictor and LST(Summer) and LST(Winter) as the less significant variables increases the goodness of fit up-to adjusted R2= 0.65(Table.5. Model 6) and similar to the NDBI the individual and ensembled contribution of

Table.5.Multiple Linear Regression models identifying the Percentage of Urbanized Area (PUA) :

	Variables	Equation	R^2/Adj. R^2	VIF		P Value
Model 1	NDBI	Predicted PUA = 48.894 + 161.615*NDBI	0.51		1.00	0.000
Model 2	MNDBI	Predicted PUA = 63.658 +68.545*MNDBI	0.56		1.00	0.000
Model 3	$LST_{(Summer)}$	Predicted PUA =-103.436 + 4.86*$LST_{(Summer)}$ + 121.536*NDBI	0.592	$LST_{(Summer)}$	1.33	0.000
	NDBI			NDBI	1.33	0.000
Model 4	$LST_{(Winter)}$	Predicted PUA = 17.607 + 5.437*$LST_{(Winter)}$ + 132.301*NDBI	0.581	$LST_{(Winter)}$	1.23	0.000
	NDBI			NDBI	1.23	0.000
Model 5	$LST_{(Summer)}$	Predicted PUA =-79.147 + 3.51*$LST_{(Summer)}$+ 3.129*$LST_{(Winter)}$ + 115.871*NDBI	0.614	$LST_{(Summer)}$	1.86	0.000
	$LST_{(Winter)}$			$LST_{(Winter)}$	1.71	0.000
	NDBI			NDBI	1.39	0.000
Model 4	$LST_{(Summer)}$	Predicted PUA =-72.244 + 4.234*$LST_{(Summer)}$ + 53.581*MNDBI	0.622	$LST_{(Summer)}$	1.39	0.000
	MNDBI			MNDBI	1.39	0.000
Model 5	$LST_{(Winter)}$	Predicted PUA = 33.310 + 4.861*$LST_{(Winter)}$ + 57.561*MNDBI	0.621	$LST_{(Winter)}$	1.26	0.000
	MNDBI			MNDBI	1.26	0.000
Model 6	$LST_{(Summer)}$	Predicted PUA =-49.570 + 2.942*$LST_{(Summer)}$ + 3.004*$LST_{(Winter)}$ + 51.376*MNDBI	0.644	$LST_{(Summer)}$	1.92	0.000
	$LST_{(Winter)}$			$LST_{(Winter)}$	1.71	0.000
	MNDBI			MNDBI	1.46	0.000

LST(Summer) and LST(Winter) improve the fit by around 2% (adjusted R2= 0,002, Table.5. Models4-6). Overall, it is evident that MNDBI is more accurate in identification of the built-up areas and with LST(Summer) the accuracy increases by adjusted R2= 0.06 around 6% (Table.5. Model 4). The p- values of all the models was p- values< 0.001 and in case of MLR, the Variance Inflation Factor (VIF) representing multi-collinearity of the variables in the model were insignificant. Thus MNDBI alone can predict 56% variations in PUA and a 0.1 increase in MNDBI values results in 6.85 increase in PUA.

Based on the correlation analysis we inquire regression models composed of primarily NDBI ,MNDBI along with other contributing indicators to check for the most accurate identification of the Percentage Building Density (PBD). The details of the modelling are summarized in Table.6.

Table.6.Multiple Linear Regression models identifying the Percentage of Building Density (PBD) :

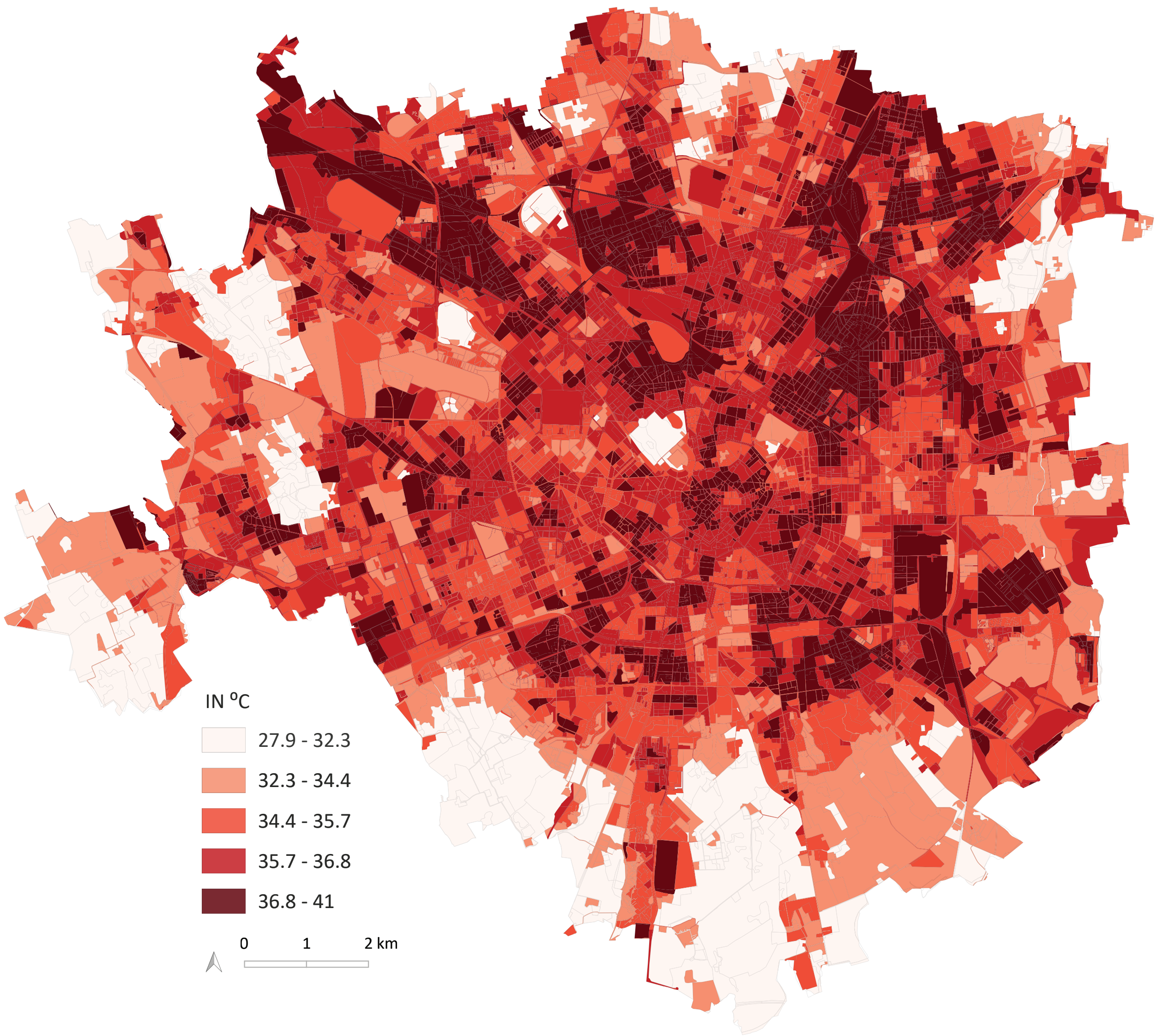
	Variables	Equation	R^2/Adj. R^2	VIF		P-Value
Model 1	NDBI	Predicted PBD = 25.164 + 133.679*NDBI	0.62	1.00		0.00
Model 2	MNDBI	Predicted PBD =-37.129+ 55.13*MNDBI	0.65	1.00		0.00
Model 3	$LST_{(Summer)}$	Predicted PBD =-49.534 + 2.382*$LST_{(Summer)}$ + 115.83*NDBI	0.658	$LST_{(Summer)}$	1.33	0.00
	NDBI			NDBI	1.33	0.00
Model 4	$LST_{(Winter)}$	Predicted PBD = 8.137 + 2.958* $LST_{(Winter)}$ + 117.729*NDBI	0.655	$LST_{(Winter)}$	1.23	0.00
	NDBI			NDBI	1.23	0.00
Model 5	$LST_{(Summer)}$	Predicted PBD = -34.724 + 1.555* $LST_{(Summer)}$ + 1.936*$LST_{(Winter)}$ + 110.451*NDBI	0.667	$LST_{(Summer)}$,	1.87	0.00
	$LST_{(Winter)}$			$LST_{(Winter)}$	1.71	0.00
	NDBI			NDBI	1.39	0.00
Model 6	$LST_{(Summer)}$	Predicted PBD =-25.631 + 1.959*$LST_{(Summer)}$ + 48.954*MND-BI	0.674	LST	1.39	0.00
	MNDBI			MNDBI	1.39	0.00
Model 7	$LST_{(Winter)}$	Predicted PBD = 20.711 + 2.629*$LST_{(Winter)}$ + 49.187*MND-BI	0.677	$LST_{(Winter)}$	1.26	0.00
	MNDBI			MNDBI	1.26	0.00
Model 8	$LST_{(Summer)}$,	Predicted PBD =-11.923 + 1.159*$LST_{(Summer)}$ + 1.898*$LST_{(Winter)}$ + 46.752*MNDBI	0.683	$LST_{(Summer)}$,	1.92	0.00
	$LST_{(Winter)}$			$LST_{(Winter)}$	1.71	0.00
	MNDBI			MNDBI	1.46	0.00

The R value of simple linear regressions model developed with individual variables MNDBI and NDBI in predicting PBD is R=0.65 and R=0.62 respectively. The multiple regression analysis (MLR) modelling of PBD with NDBI as the significant predictor and LST(Summer) and LST(Winter) as the less significant variables increases the goodness of fit up-to adjusted R2= 0.67(Table.6. Model 5). But, the contribution of the less significant variables in the models, the LST(Summer) and LST(Winter) either individually and together improve the adjusted R2 by only 0.01 roughly 1% (Table.6. Models3-5).

However, the MLR model with MNDBI as the significant predictor and LST(Summer) and LST(Winter) as the less significant variables increases the goodness of fit up-to adjusted R2= 0.68(Table.6. Model 8) and similar to the NDBI the individual and ensembled contribution of LST(Summer) and LST(Winter) improve the fit by around 2% (adjusted R2= 0,002, Table.6. Models6-8). Similarly in case of PBD also, it is evident that MNDBI is more accurate in identification of the built-up areas and with LST(Summer) the accuracy increases by adjusted R2= 0.02 around 2% (Table.6. Model 6). The p- values of all the models for PBD regressions analysis was p- values< 0.001 and in case of MLR, multi-collinearity of the variables in the model were found to be insignificant.

Thus MNDBI can predict 65% variation in PBD and a 0.1 increase in MNDBI leads to PBD values increasing by 5.513 .

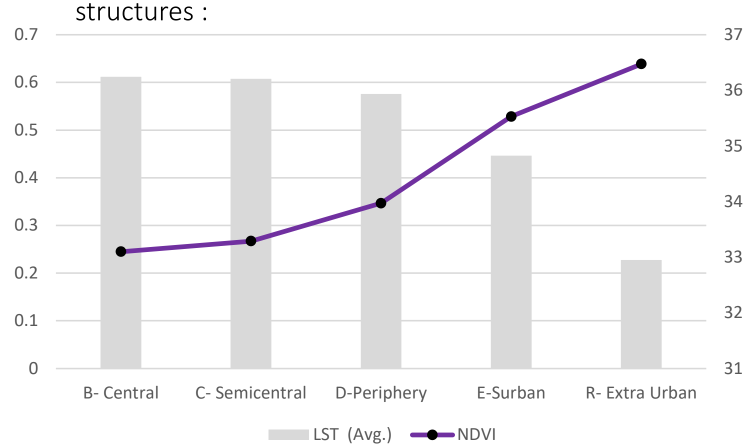
Map.11 .Land Surface Temperature (LST) :



5.7.Land Surface Temperature (LST) :

In this section we observe the various urban hotspots of summer surface temperature in Map.11. and analyze the spatial distribution of LST across the spatial categories with emphasis on the contribution of the extent of vegetative cover. illustrated in Fig.16. Literature has provided conclusive evidence that extensive urbanization account for higher temperatures and heat island effect. Consequently, Land surface temperature values of Milan increase with increase in built-up areas with a moderate positive correlation of r= 0.57 and decrease with increased vegetations with NDVI values at r= - 0.58. This is also reflective in Fig.7 the spatial configuration of the built environment where surface temperature is higher in the central zone and reduce as we move towards the suburbs and exurbs. The surface temperature does not exhibit significant correlation with Population and Household densities r= 0.19 and r=0.20 respectively, that would have accounted for spaces of sustained thermal discomfort exposure of the residents.

Fig.16.LST vs NDVI distribution across urban spatial structures :



5.8.Building Energy Certification Class :

Fig.17.Reasons for APE productions :

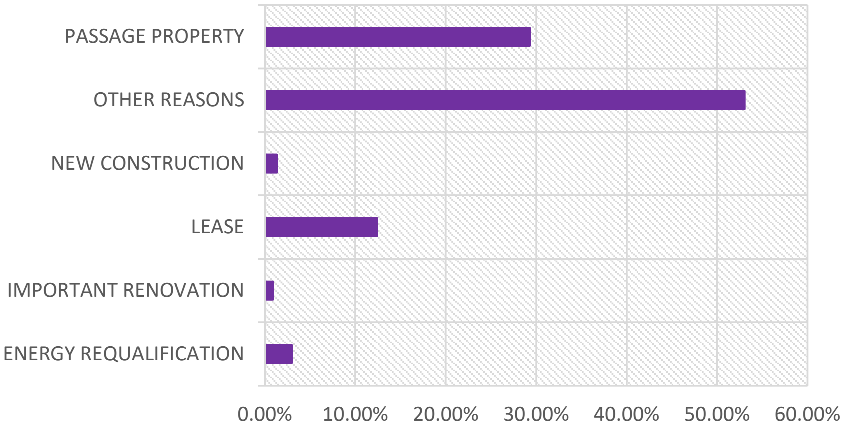
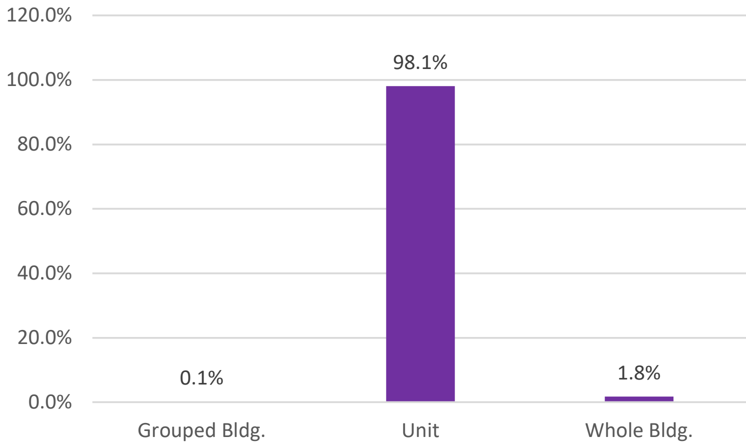


Fig.18.Real-estate type of the produced APE certifications :



Here, Fig.17. describes the reasons mentioned for production of energy certification and Fig.18 represents the real-estate type for which most certifications have been registered. From Fig.8. we observe that very few building energy efficiency certifications are produced for energy requalification, renovations and new construction, while larger proportions are produced for the legislative process of lease and property transactions. A significant portion listed for other purposes could reflect short rental contract which do not specifically fall under the lease category, especially considering the influx of international and national student community that the universities programs of Milan incur.

It is important to interpret if the impetus for energy certification productions has disseminated across the masses to ensure a robust foundation to drive the shift to sustainable energy consumption and emission reductions. As predominantly the certifications are produced for individual real-estate unit Fig.18, we explore this scenario by hypothesizing the household densities as proxy variable for individual real-estate units and find its correlation the number of certifications produced. We find a significant positive correlation r= 0.64, reflecting that where the household densities are more the higher the proba-

Fig.19.CO_2 Emissions according to realestate type :

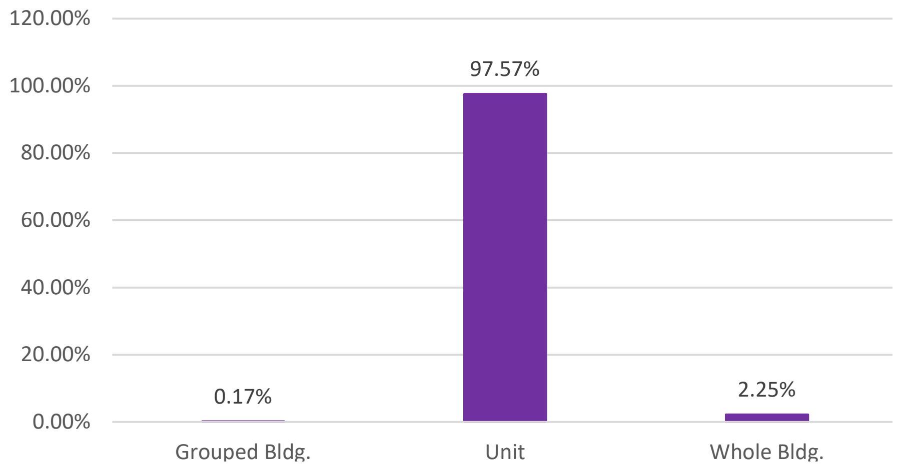
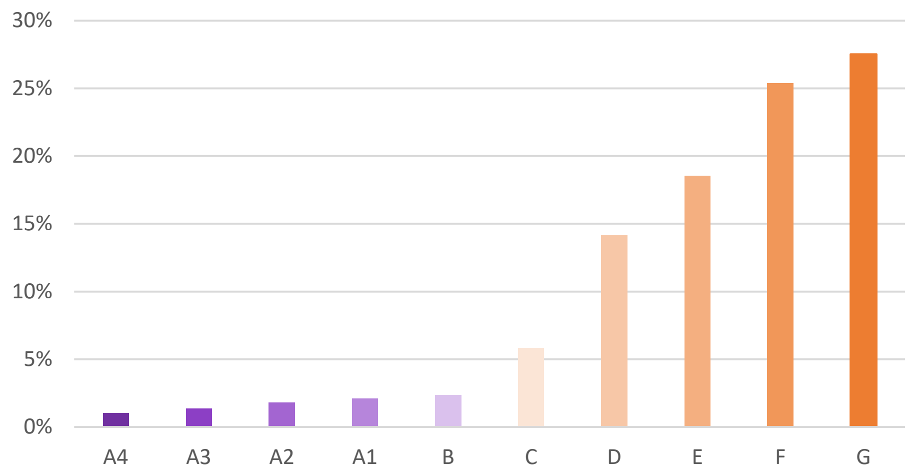


Fig.20.No.of Certifications under each classNo.of Certifications :

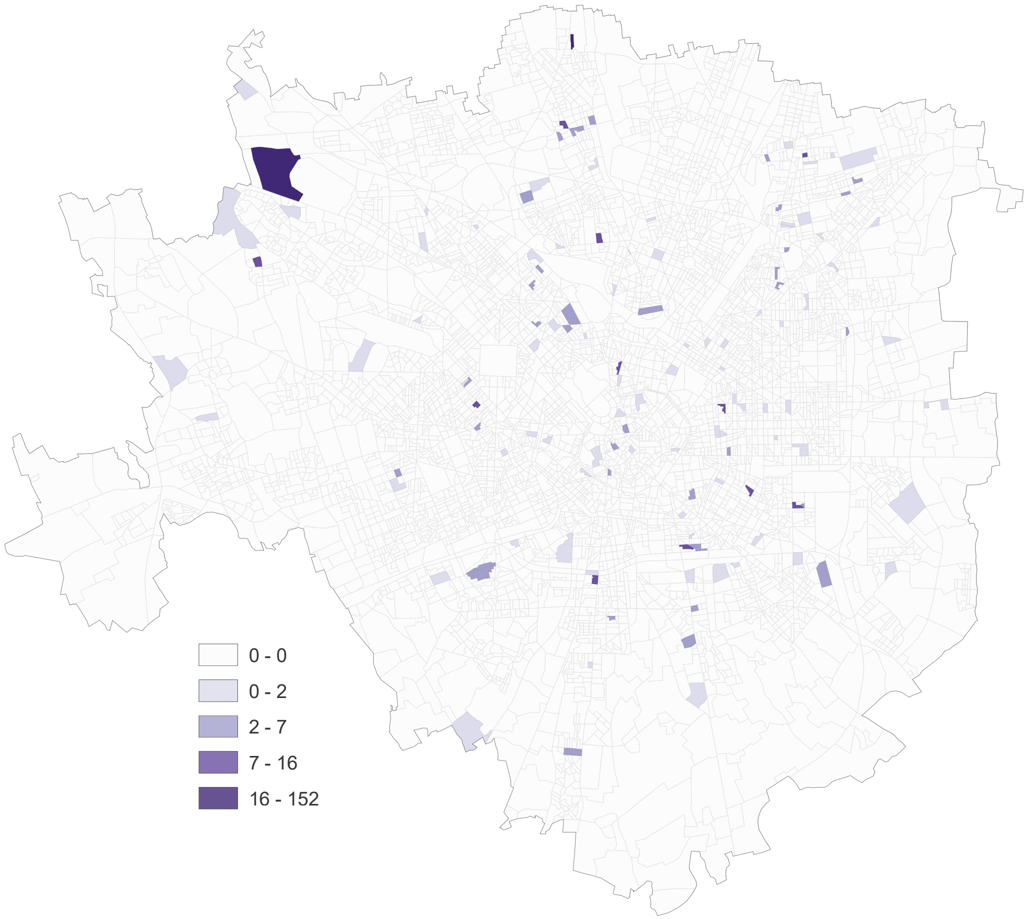


bility it is for them to obtain an energy efficiency certification.

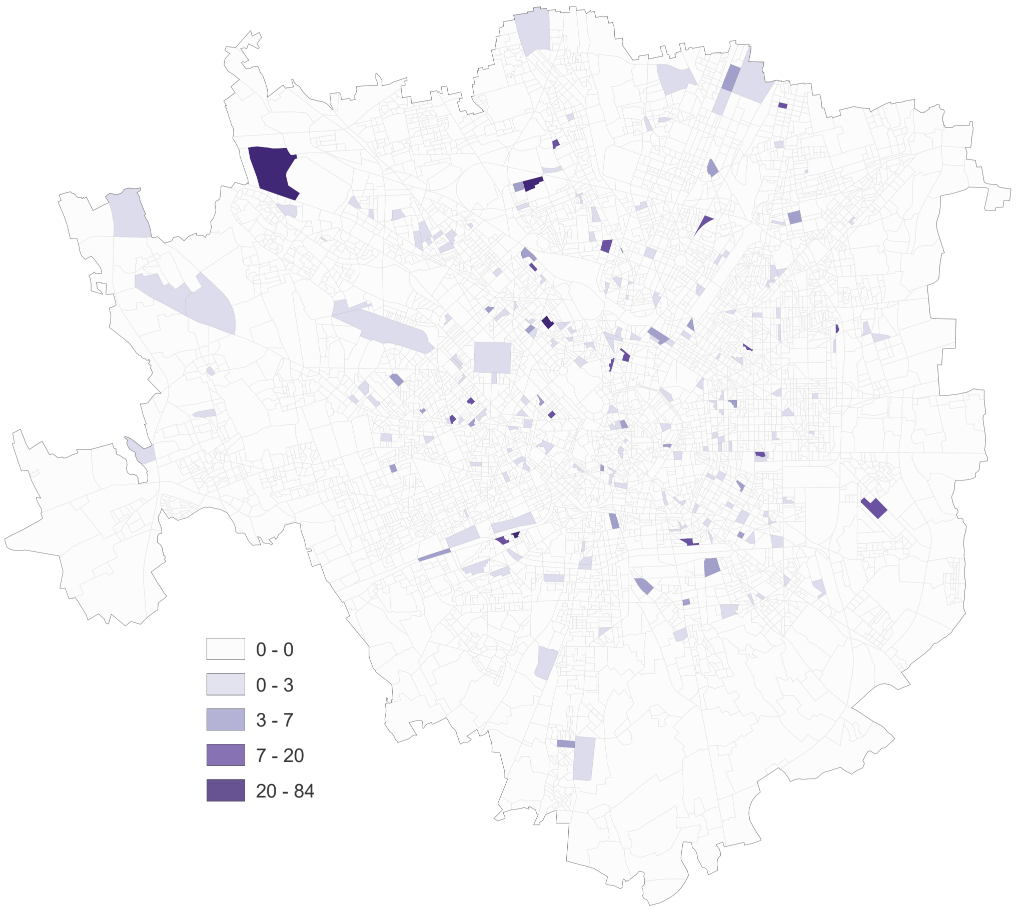
Fig.19. represents the level of carbon emissions of the real estate types while, Fig.20. illustrates the energy performance class of the certification and the number of certifications issued under each. From the total energy certification issued majority fall under lower performances classes irrespective of the real-estate type as represented in Fig.20. This may be due to the obligatory requirement of the certifications during registrations of letting contracts where the motivation on improving the performance is diminished as 83% of the certification are for residential use and only 17% are commercial. which is also reflected in the average co2 emissions for the three-real-estate type in Fig.19. which are comparably significant for unit type. Energy consumption for the residential sector has shown an increasing trend, but our analysis reflects the need to incentivize requalification and ameliorate energy performances. However, in the light of Italy's National Energy Resilience and Recovery plan under the 'Green revolution and Ecological transition' mission which target the energy efficiency transformation of about 100,000 private buildings, could yield better outcome.

Illustrated in the Map.12 and 13 are the number of building energy efficiency certitications isuued under A4 and A3 energy class respectively within each census block group.

Map.12 .No. of Building certifications under A4 Class
(assigned numeric value 10) :

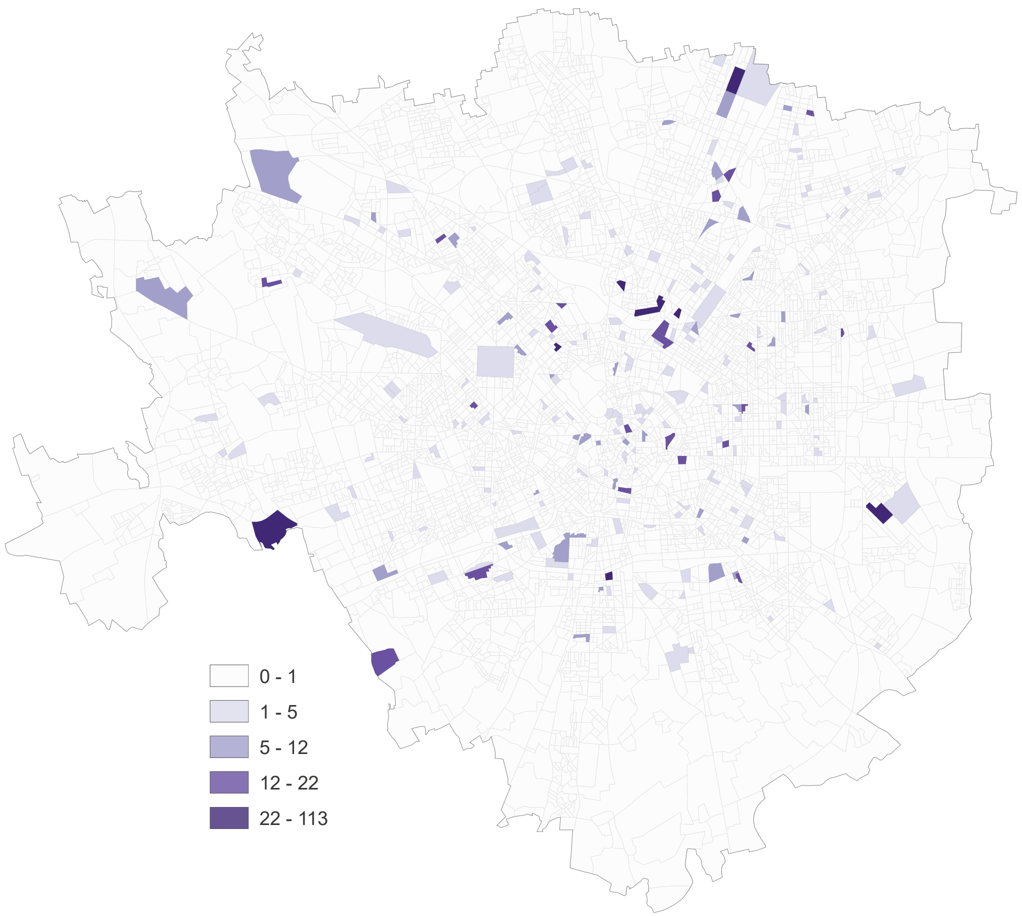


Map.13 .No. of Building certifications under A3 Class
(assigned numeric value 9) :

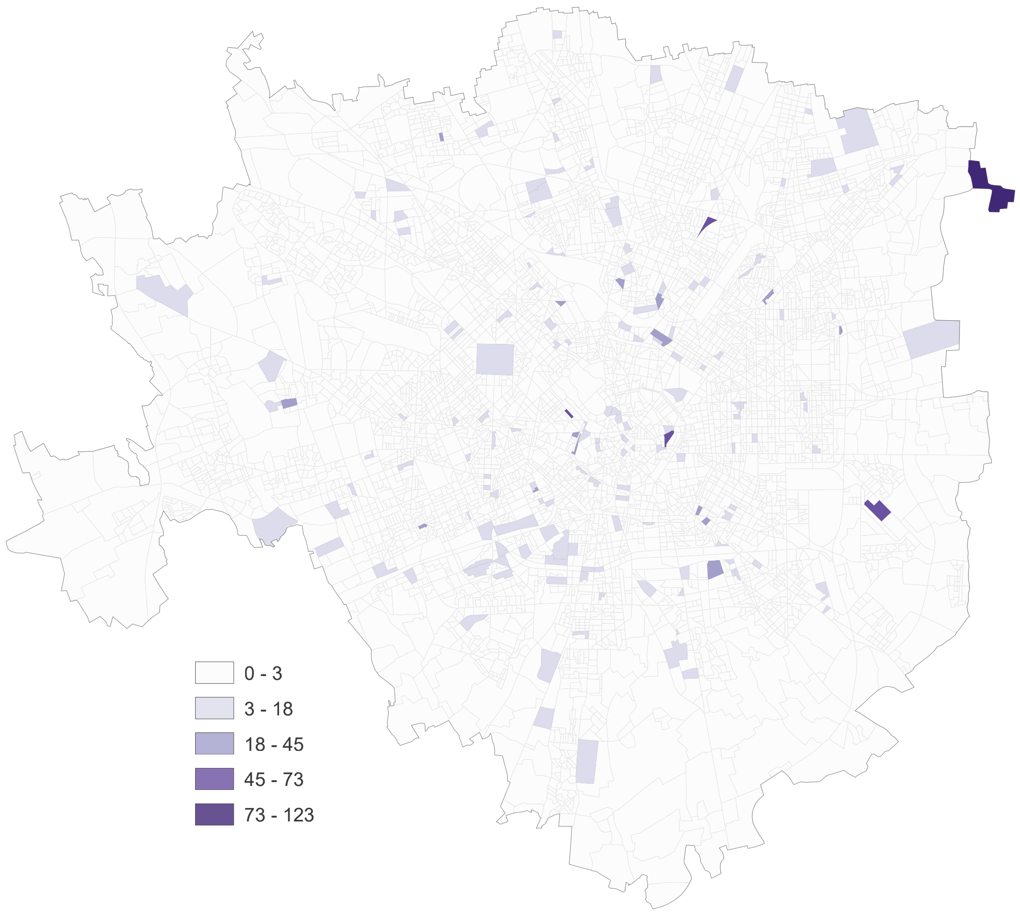


Illustrated in the Map.14 and 15 are the number of building energy efficiency certitications isuued under A2 and A1 energy class respectively within each census block group.

Map.14 .No. of Building certifications under A2 Class (assigned numeric value 8) :

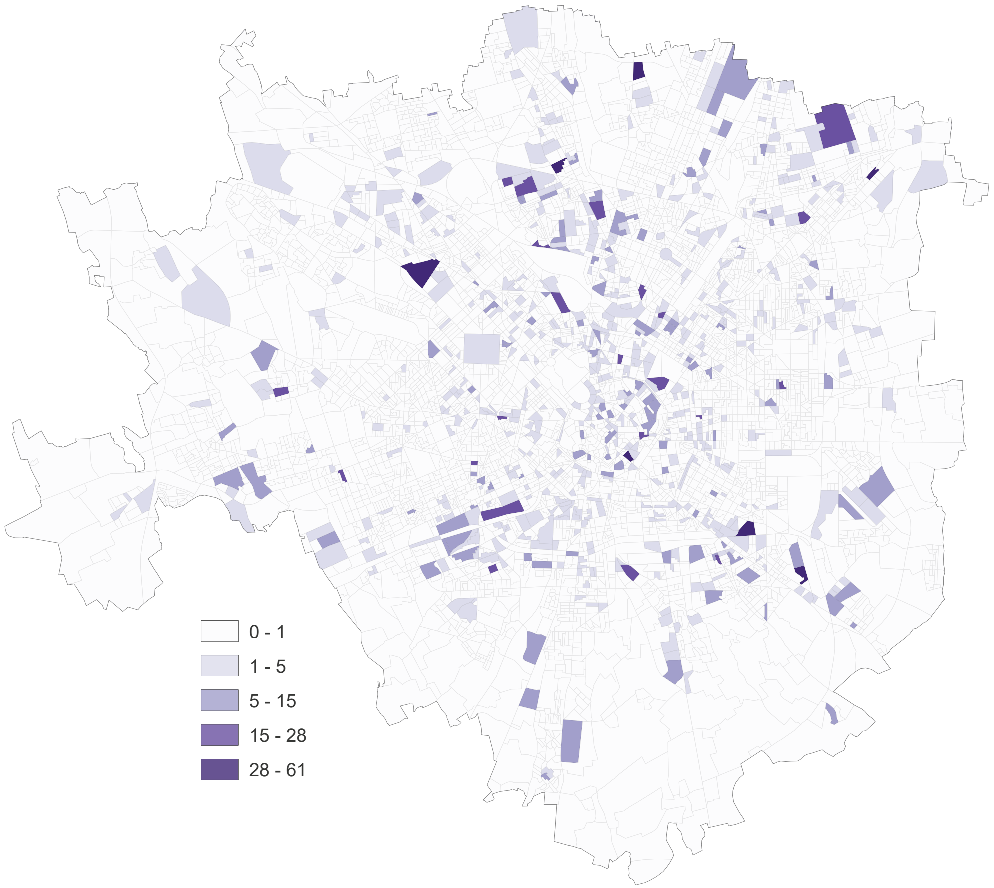


Map.15 .No. of Building certifications under A1 Class (assigned numeric value 7) :

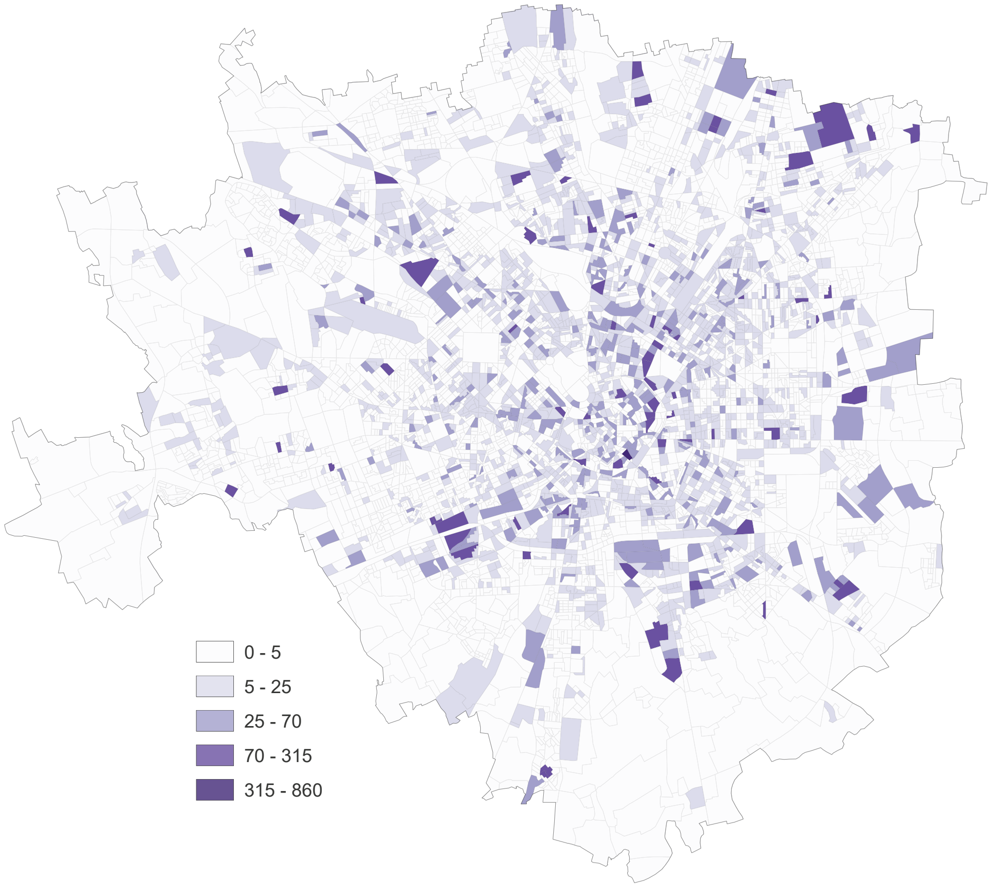


Illustrated in the Map.16 and 17 are the number of building energy efficiency certitications isuued under B and C energy class respectively within each census block group.

Map.16 .No. of Building certifications under B Class (assigned numeric value 6):

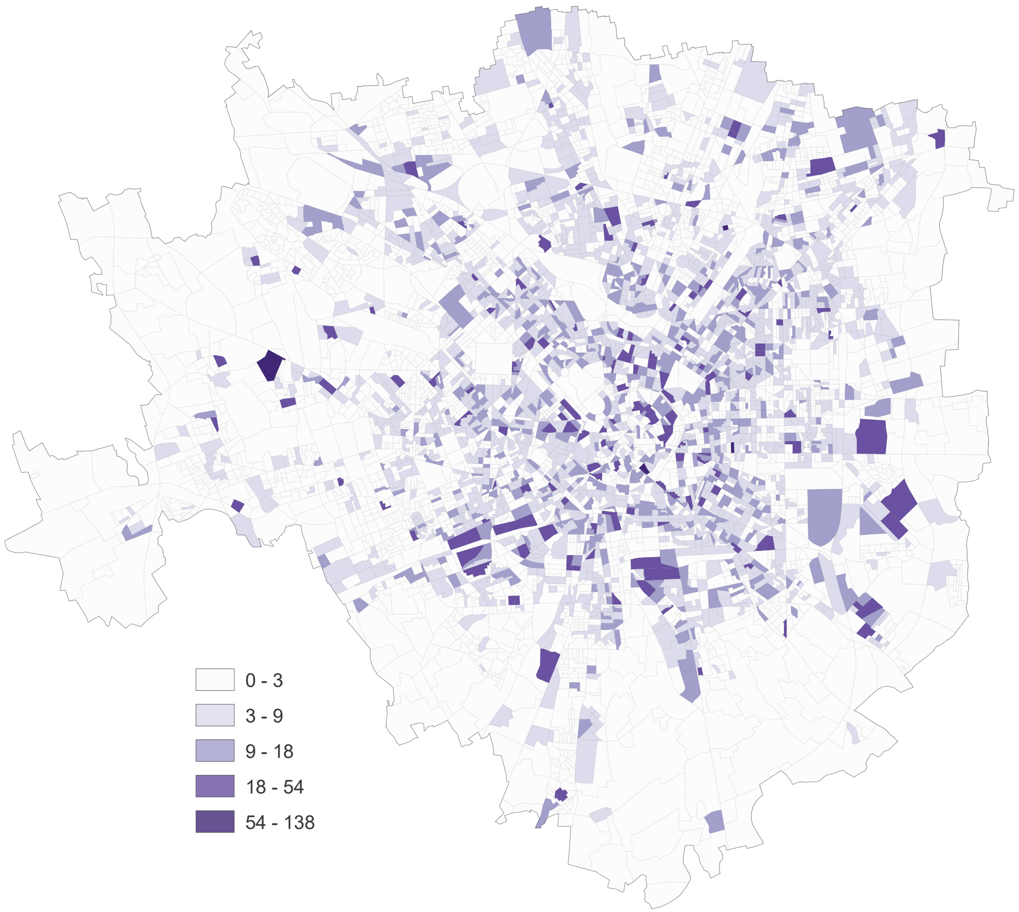


Map.17 .No. of Building certifications under C Class (assigned numeric value 5) :

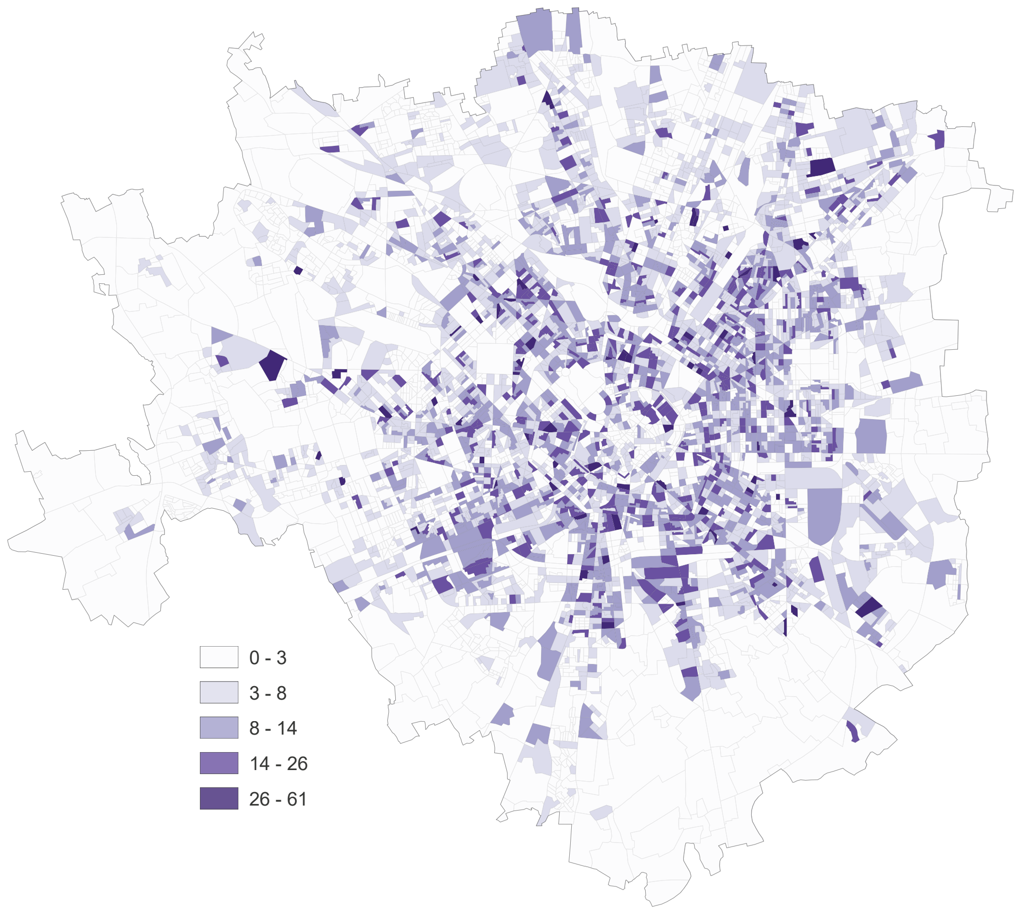


Illustrated in the Map.18 and 19 are the number of building energy efficiency certitications isuued under D and E energy class respectively within each census block group.

Map.18 .No. of Building certifications under D Class (assigned numeric value 4) :

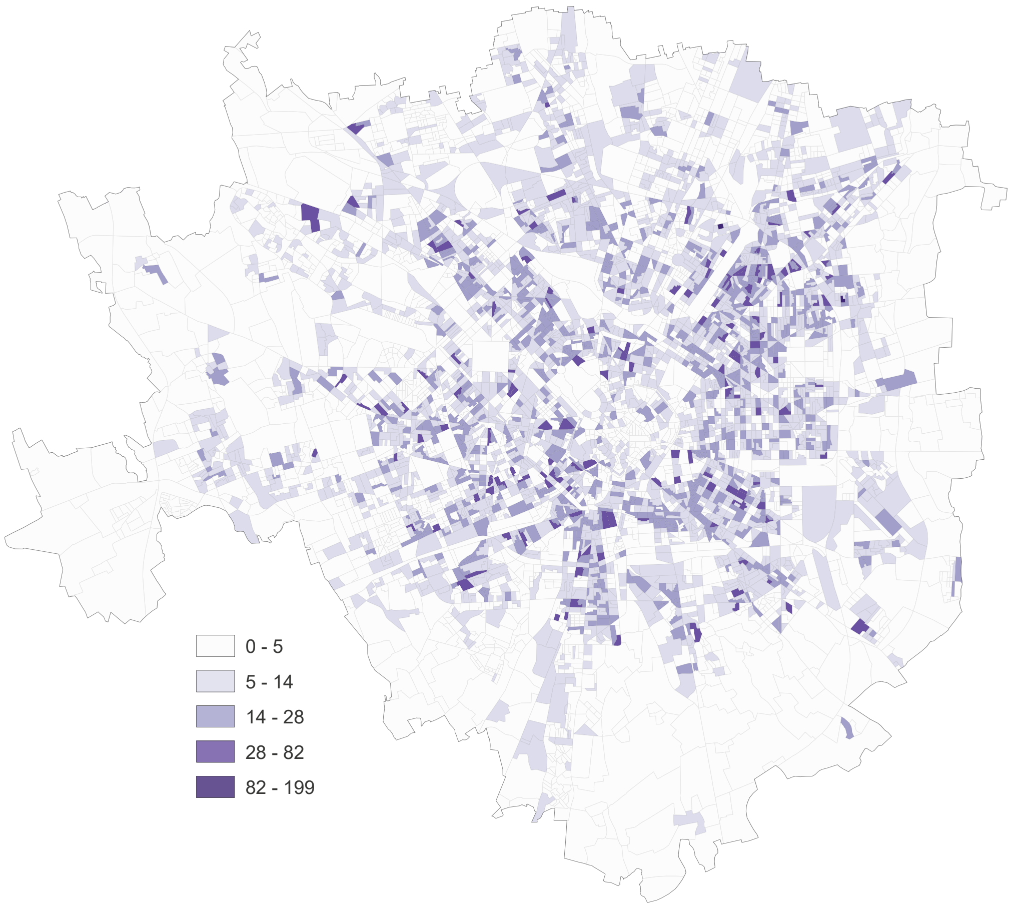


Map.19 .No. of Building certifications under E Class (assigned numeric value 3) :

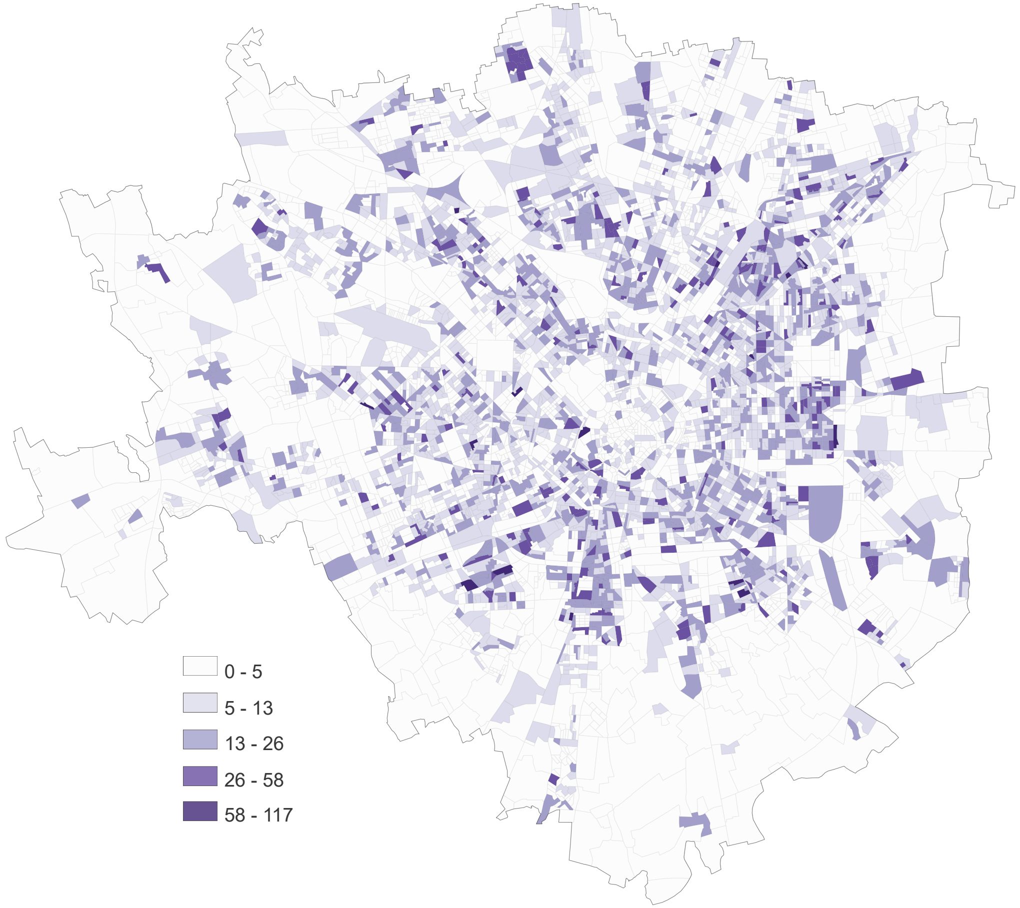


Illustrated in the Map.20 and 21 are the number of building energy efficiency certitications isuued under F and G Eenergy class respectively within each census block group.

Map.20 .No. of Building certifications under F Class (assigned numeric value 2) :



Map.21 .No. of Building certifications under G Class (assigned numeric value 1) :



Map.22. defines the overall Building Energy efficiency numeric rating aggregated of all certifications with each census block group derived from its categorical energy classe. Fig.20. highlights the inherent drawbacks associated with this analysis by presenting the rate of geolocation of various energy class.

As energy efficiency ratings are performance descriptive no significant inference were obrained from the spatial correlations of BEER from Map.22. Except that the overall certification are low for higher performance class, their cumulative spatial distribution analysis is biased and the validity of the aggregated values is reduced as the rate of geo-locations of the higher classes of certification in the dataset is low Fig.20, due to missing values location details.

Map.22 .Building Energy Efficiency Rating (BEER) :

Fig.21.Rate of geo-locations of the Energy Efficiency classes :

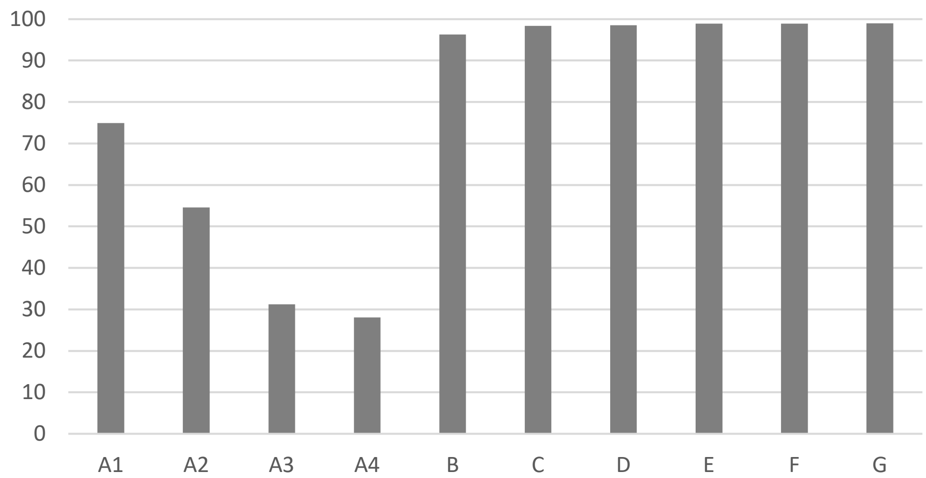


Fig.22.Energy Eficiency performance of buildings according to Age of the structures <1800 years :

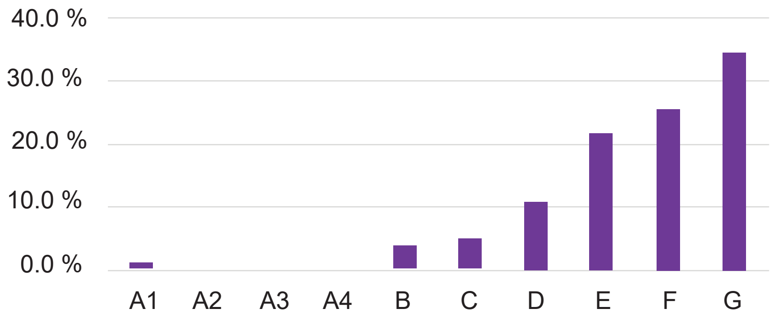


Fig.23.Energy Eficiency performance of buildings according to Age of the structures 1800- 1920 :

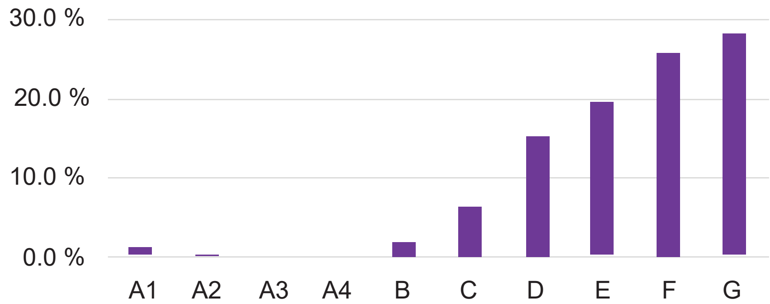
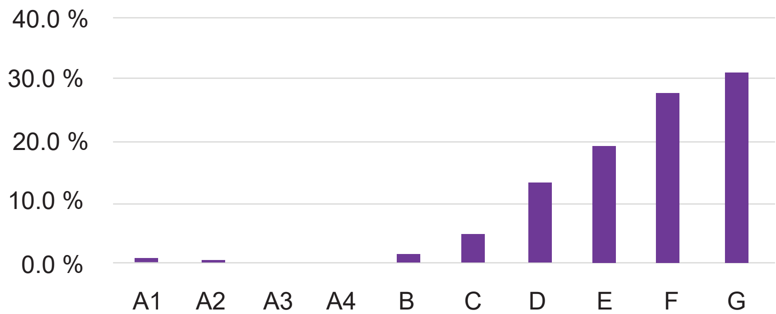


Fig.24.Energy Eficiency performance of buildings according to Age of the structures 1920- 1980 :



Presented anti-clockwise from the top is the bi-variate analysis of number of buildings categorized according to their year of construction and their current energy performance class. Further, analysis was carried out analyzing the Building Energy Efficiency Rating and the state of conservation of buildings from the census data. Their correlation analysis yielded r=0.05 a positive yet insignificant correlation. This is because significant number of buildings are categorized to be in the better conservational state spectrum. And from analysis the energy performance of buildings according to age Fig.21,22,23,24. we infer that the buildings constructed before the 1980 predominantly have lower energy performance classes. While in the buildings constructed from 1980-2021, we observe a drastic change in the trend with increased number of higher energy performance class and decreased lower energy classes.

Fig.25.Energy Eficiency performance of buildings according to Age of the structures 1980-2021 :

5.9.Urban Functionality Diversity (UFD) :

Map.23. presents the number of functions within each block group as the richness of functional diversity(UFD). Fig.25. demonstrates the diversity according to the municipality level. The correla-tion analysis between Urban Functional Diversity (UFD) and Population and Household densities (PD and HD) exhibit an insignificant relationship with r=0.09 and r=0.15 respectively. The Hypoth-esis that higher functional diversity would lead to higher property valuations is weak to sustain with a weak yet positive correlation of r=0.36. Areas with higher diversity of function are ob-served to have higher built-up and green areas with a strong positive correlation of r=0.63 and 0.64 respectively. However, the most significant result is that functional diversity is strongly re-lated to the linear distance from the historic core to the peripheries, with a strong negative cor-relation r=-0.82. This implies that as the distance from the center increases the functional diver-sity of the urban fabric becomes sparse.

Map.23 .Richness of diverse urban functions :

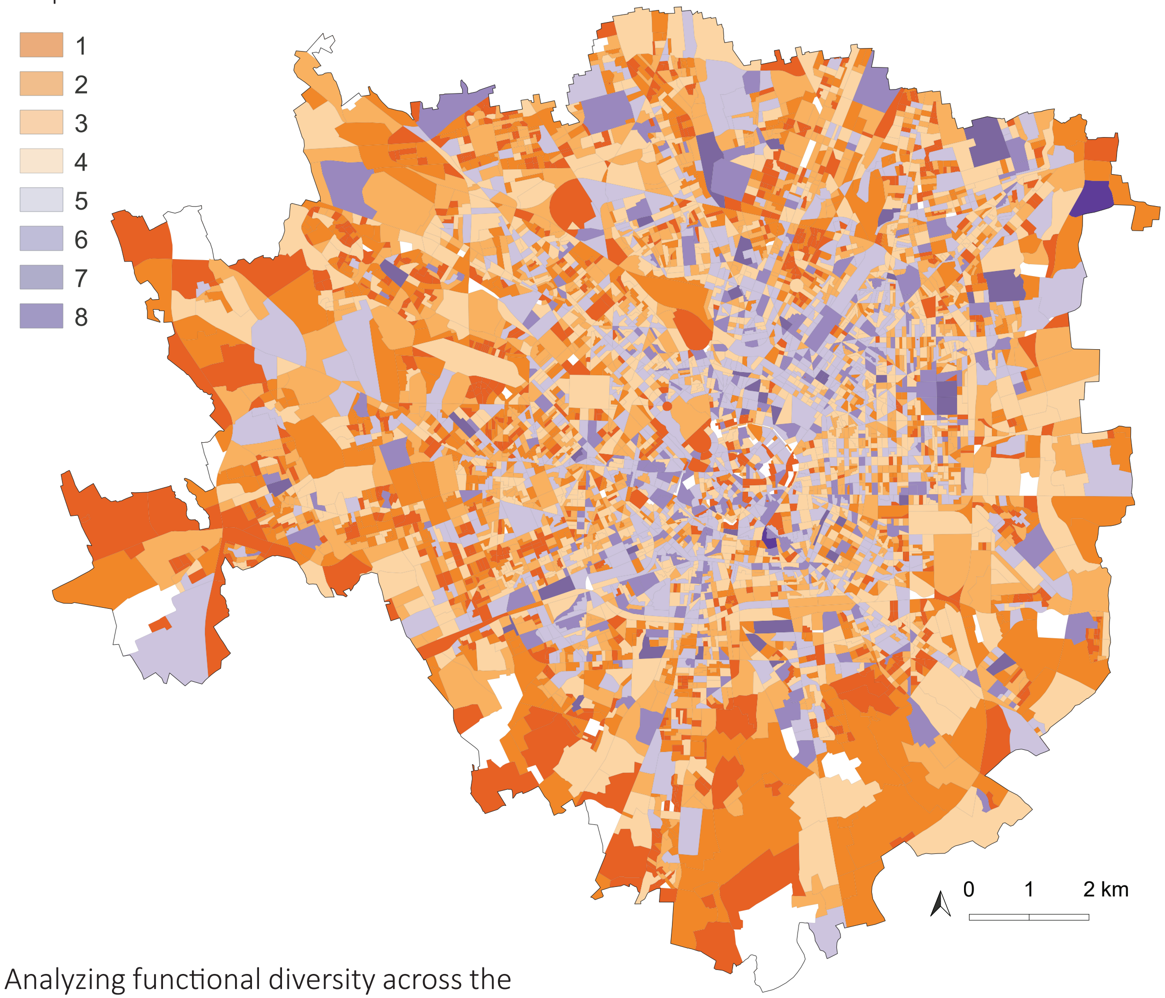
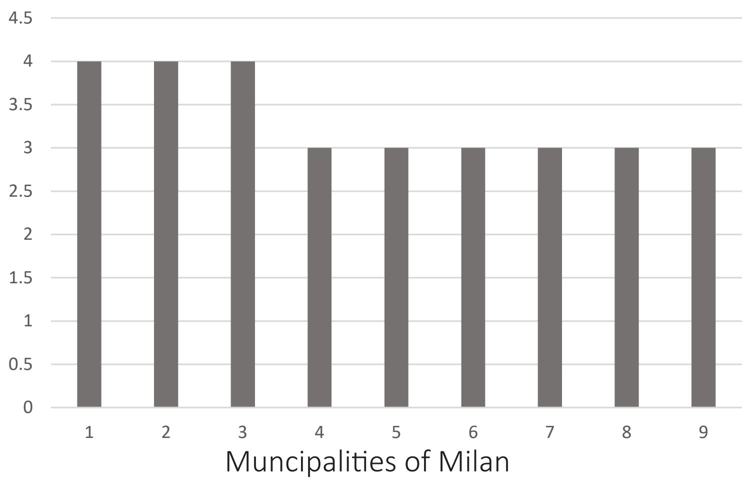


Fig.26.Predominant functional diversity in each municipal zone :



Analyzing functional diversity across the municipal zones Fig.25. we observe that the majority of blocks in the municipal zones have utmost three functionalities, with the zones one, two and three having four functionalities. Thus, the overall urban functional diversity score of Milan is 0.35 Table.7.

Table.7.Functional Diversity score of Milan :

Sum $Pres_i$ =	Presence of all the functions in ' i'
Pop_i =	Fraction of Population in 'i'
Weighted sum =	$\sum SumPres_i * Pop_i = 3.511$
FDS =	Weighted sum/10= 0.35

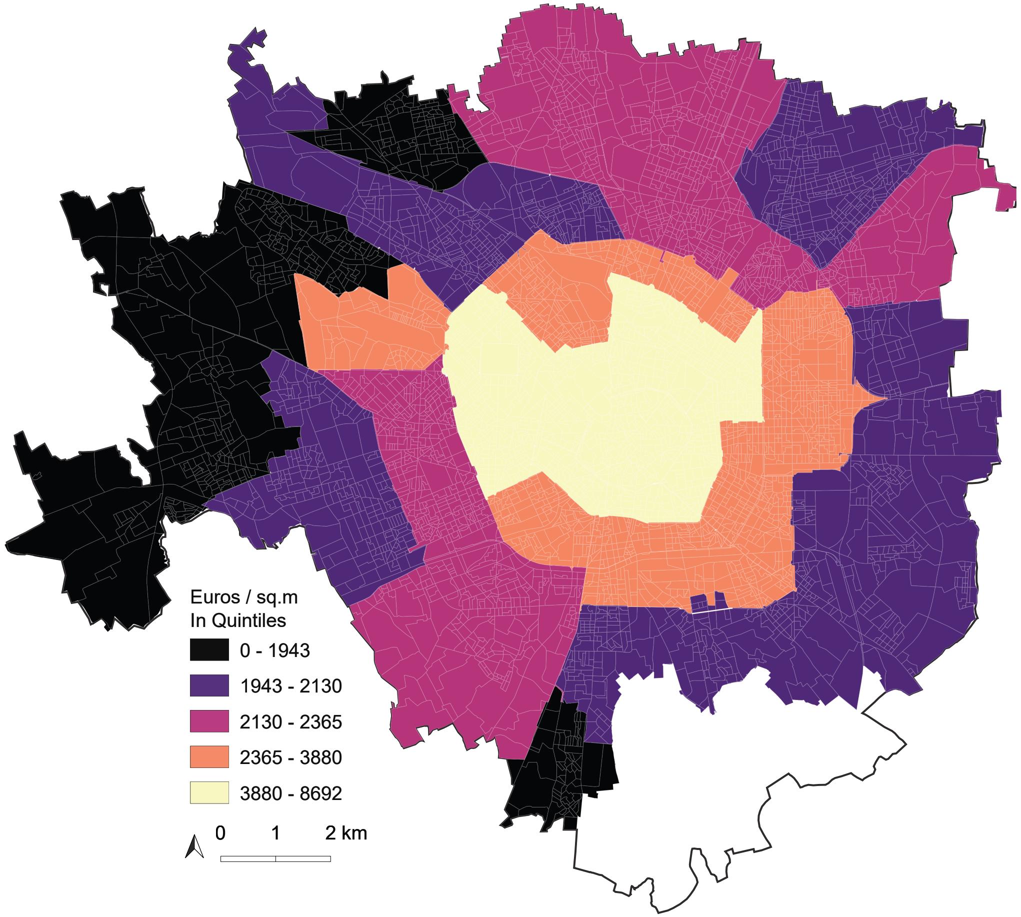
Presented in Map.24 is the spatial distribution of 2021 annual Residential Property Values(R.P.Val.) in euros for every square meter. As we can observe the property values are concentrated in the center. From the correlation analysis we can infer that residential property values are the most negatively correlated with the distance from the city center at around r=-0.78, being measured from Piazza Duomo, the values decrease as the distance from the center increases. The next inference is that the along with the distance, the NDVI values are also inversely correlated with R.P.Val around r=-0.66. The correlation of R.P.Val with the available area of park around r=47 a relative strong correlation. Hence, we infer that residential property values increases with area of park availability, but within the same census block the vegetative cover reduces.

Similarly, a moderately strong positive correlation of R.P.Val is observed with the building indices, the MNDBI and Urban functional Diversity (UFD) each around r=0.64 reflecting that the more the built area and the more the functional diversity in the census block group, the more its residential property values are. The property values are also related though not significantly yet negatively to the Population density (PD) r=-0.26 and Household densities HD) r=-0.3, indicating a less crowding or congested living and more availability for ease of spatial movement. The R.P.Val reflect a weak positive correlation with energy efficiency rating r=0.15, Though the relation is positive as the significance is low we can-not infer that higher energy efficiency contribute to increased R.P.Val.

Also, the relationship with the availability of the number of transits stops, the bus and tram stops, the highspeed railway stations is negatively associate to the (R.P.Val.) respectively around a relatively moderate r=-0.47 and weak r=-0.31. However insignificantly correlated to the availabil-ity of Metro / subway railway stations around r=0.6 indicating that the properties with higher values might be the limited

5.10.Residential Property Value (R.P.Val.) :

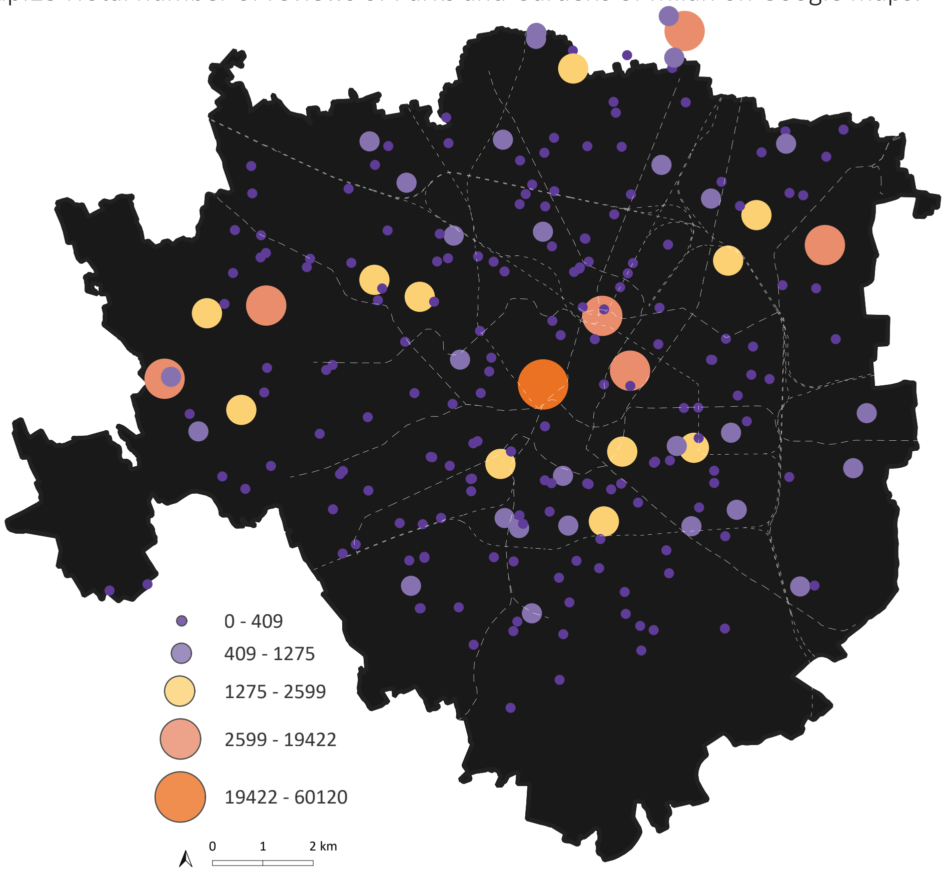
Map.24 .Residential Propery values (R.P.Val)



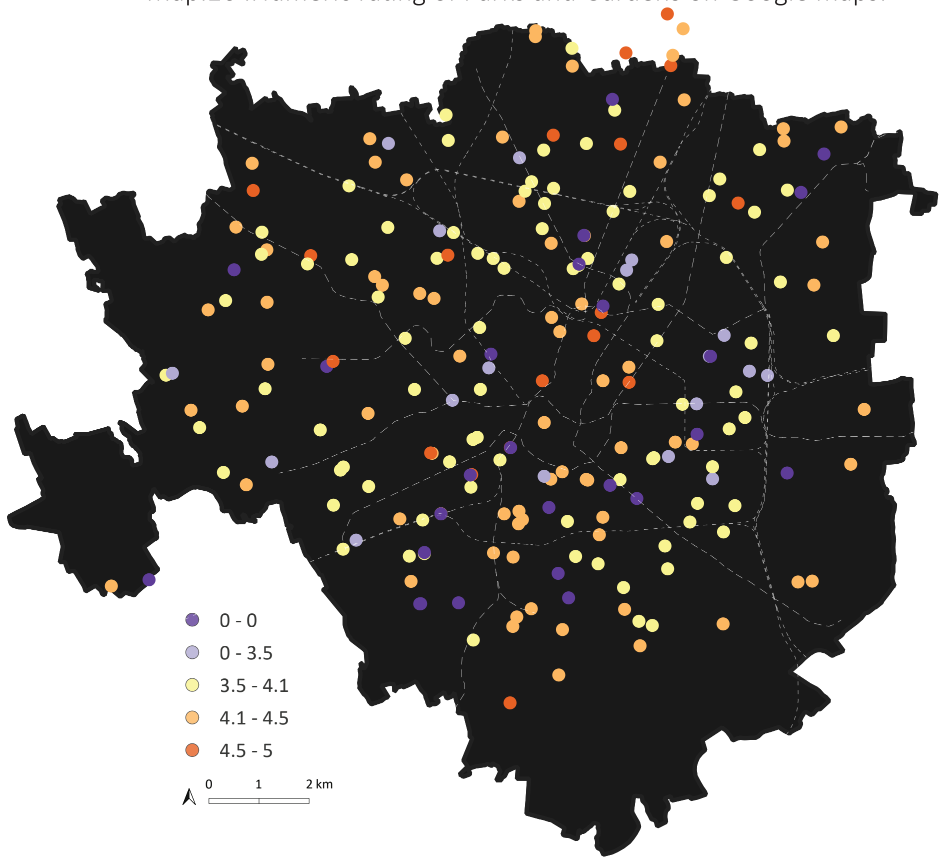
traffic zone imple-mented old historic center of Milan, Owing to the city's history with neighborhood gentrifications since the 1960's -1970's the increase in the property values from the historic center outwards, the strong mono-centric concentration of commercial activity in the same with the title of 'Fashion Capitol' reflect a retained trend of speculation and conspicuous consumption of residential assets.

5.11.Sentiment analysis of Urban Public Greens :

Map.25 .Total number of reviews of Parks and Gardens of Milan on Google maps:



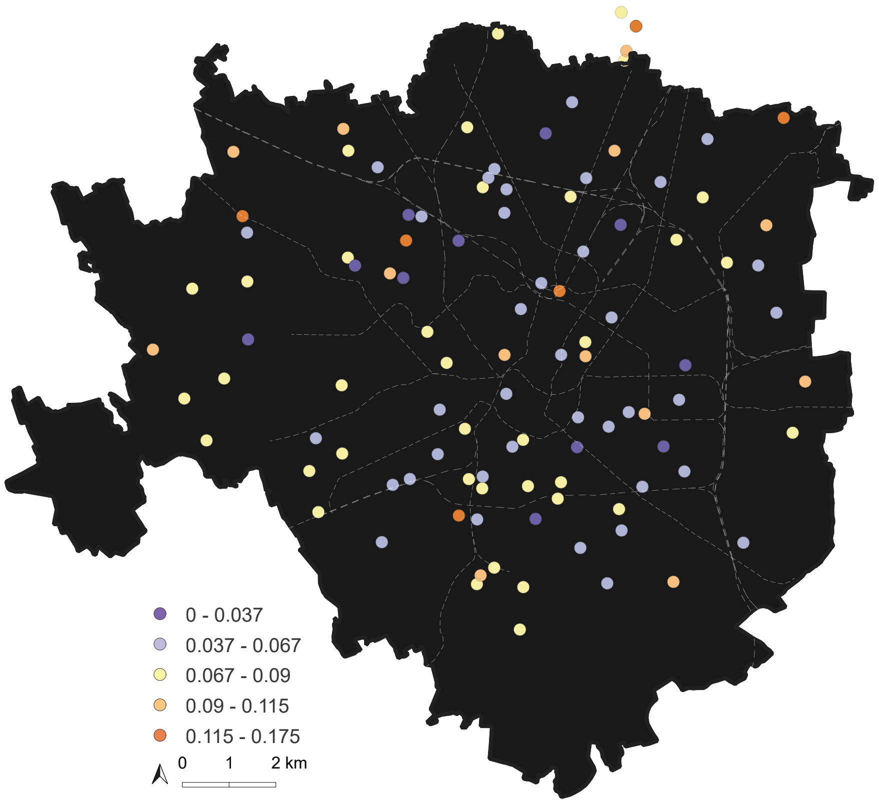
Map.26 .Numeric rating of Parks and Gardens on Google maps:



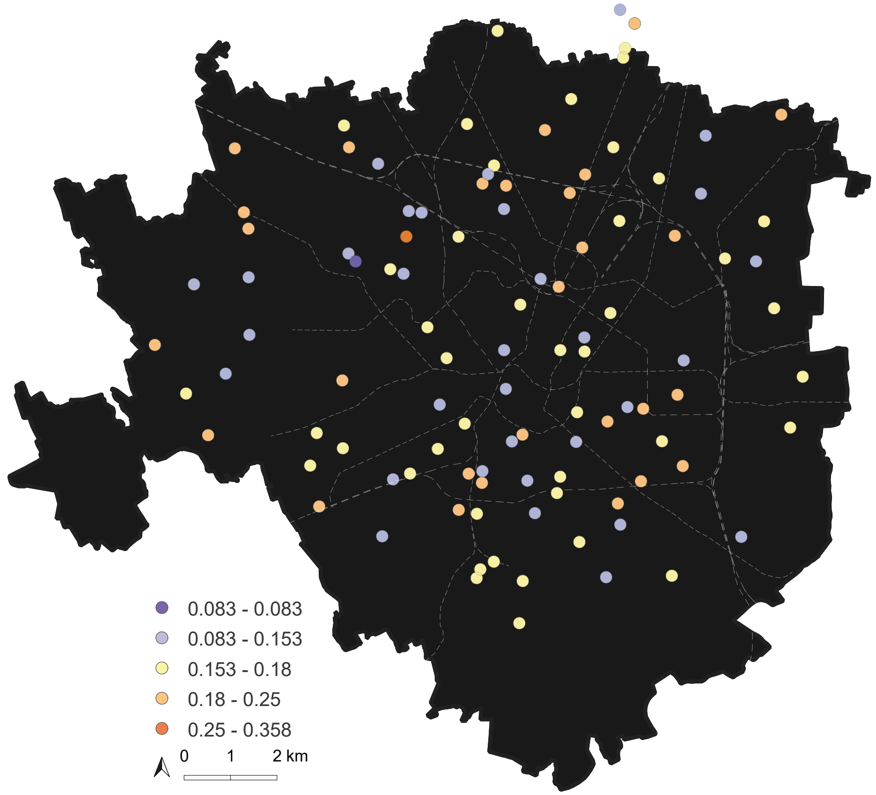
Presented in Map.25. is the total number of ratings received by the parks and garden in Milan and in Map.26. their numeric star ratings. Parco Sempione being an outlier with most reviews 60120, followed by Giardini Indro Montanelli with 19422 reviews, Parco Lambro with 4986 reviews, Parco Biblioteca degli Alberi with 3325 reviews, Parco Aldo Aniasi with 3292 reviews making the top five most reviewed Parks of Milan. The total number of reviews in google maps is aggregated through years of park and garden operational commencement and will not include any recently recognized or operationalized park or garden.

They could be attributed to the most populous and recognized public open space. However, as the most reviewed they do create a potential tourist niche as popular hotspots. Spatially they seem to form five clusters, one centrally located, three at the peripheral, one sub-peripheral around Bovisa. The three peripheral clusters are Parco Nord to the north, Parco Lambro to the east, to the west around Boscoincitta, Parco Aldo Aniasi and Parco della cave. Map.26. demostrates the acquired star ratings of the parks and gardens.

Map.27 .Polarity of Parks and Gardens Google map reviews:



Map.28 .Subjectivity of Parks ans Gardens google map reviews:

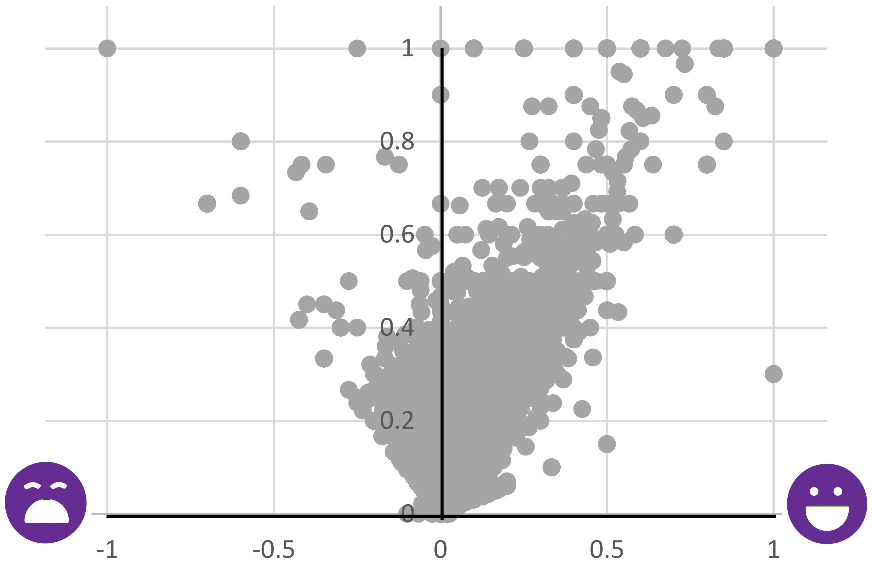


The total number of reviews received by the park or garden, do not correlate with the numeric ratings r=0.20, hence we cannot state that, if a park receives more reviews it would attribute to its higher or lower park satisfaction that would reflect in the numeric ratings. Hence, we further analyze the written reviews to form conclusive pointers to comprehend the park and garden visitors' expectations and perceptions of the space.

Map.27. Indicated the Polarity of the reviews as the predominant sentiment acquisition of each park and garden considered after the threshold valuation of a minimum 50 reviews obtained by the park or garden and posted online within four years. While, Map.28. reflects on the subjectivi-ty orientation of the review, in this case it describes if the sentimental polarity is based of subjective experiences or objective depictions of en-dogenous attributes of the parks and gardens.

Further, the polarity rating values of park and garden reviews indicate a neutral scenario. It could also reflect a n evolving scenario where with time and managerial improvements or the lack of could have led to higher or lower ratings. A time series analysis of this trend could be essential to outline the progress or the deterioration of the public open spaces.

Fig.27. Sentimental polarity vs subjectivity of reviews :

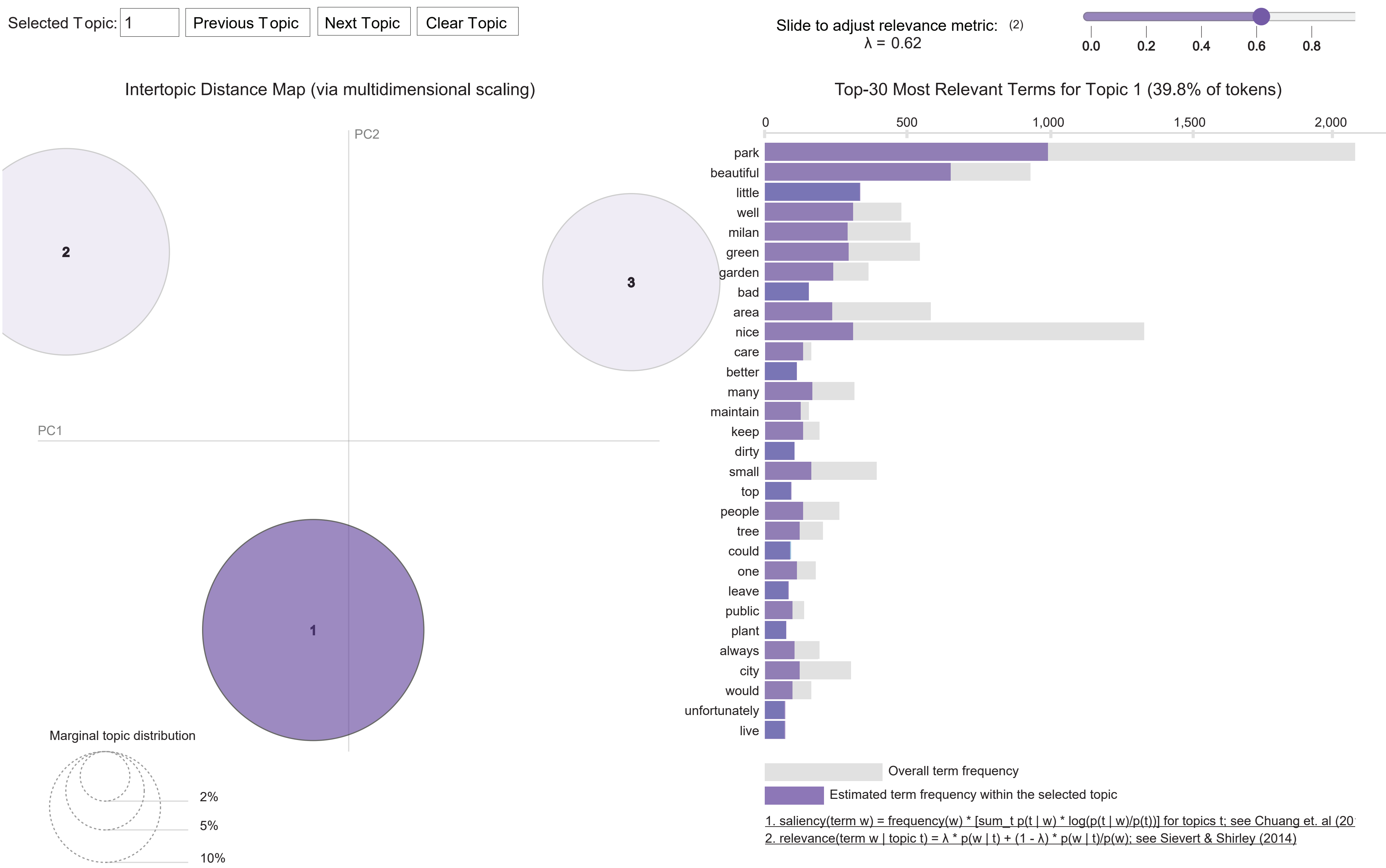


From the analysis of the subjectivity of the reviews of the Parks and Garden Fig.26 it can be noted that the reviews are predominantly objective and further analysis of the reviews could be a possible tool to understand the recreational behavioral patterns and expectation of park and garden visitors, their perception of space and may bring us a step closer to their points of concern, possible needs and scope of improvement for better management of the urban green infrastructure.

The Polarity versus subjectivity analysis of all the reviews reflect that the opinions of the reviews are for the most part neutral in int polarity and fairly objective. However most positive polarity of the reviews is more subjective that the negative polarity, this would mean the negative opinions are associated with factual context of the opinions and further analysis could form bases of concrete problem definitions. This is the briefly outlined in the topic modelling results in the following section. Based on the reviews we observe three distinct topics. Namely relating to physical aesthetic and maintenance attributes of the parks and gardens, opportunities associate with park and garden usability about the activities that are or could be carried on. And finally, describing the physicality of the specific areas of parks and gardens dedicated for children and dogs.

In each of the following pages to the left is the visualization of the inter-topic distance denoting the topic size and the significant variation in the definitions of the topic marked by its distance from other topics. As a general rule of thumb, the wider the topic cluster are spaced the better is the goodness of fit of the LDA topic model. To the right of this is a graphic description of the most relevant words that define each topic and its corresponding frequency with that particular topic.

Fig.28.Topic modelling- Model 1- Physical attributes of the parks and gardens :



The results of LDA model generated three unique topic clusters, in each fig. bellow to the left are indicated the topic clusters, as a general rule of thumb, the wider apart they are pictorially represented the better the model performs. And to the right of each fig. are represented the top thirty words and their frequency in the topic.

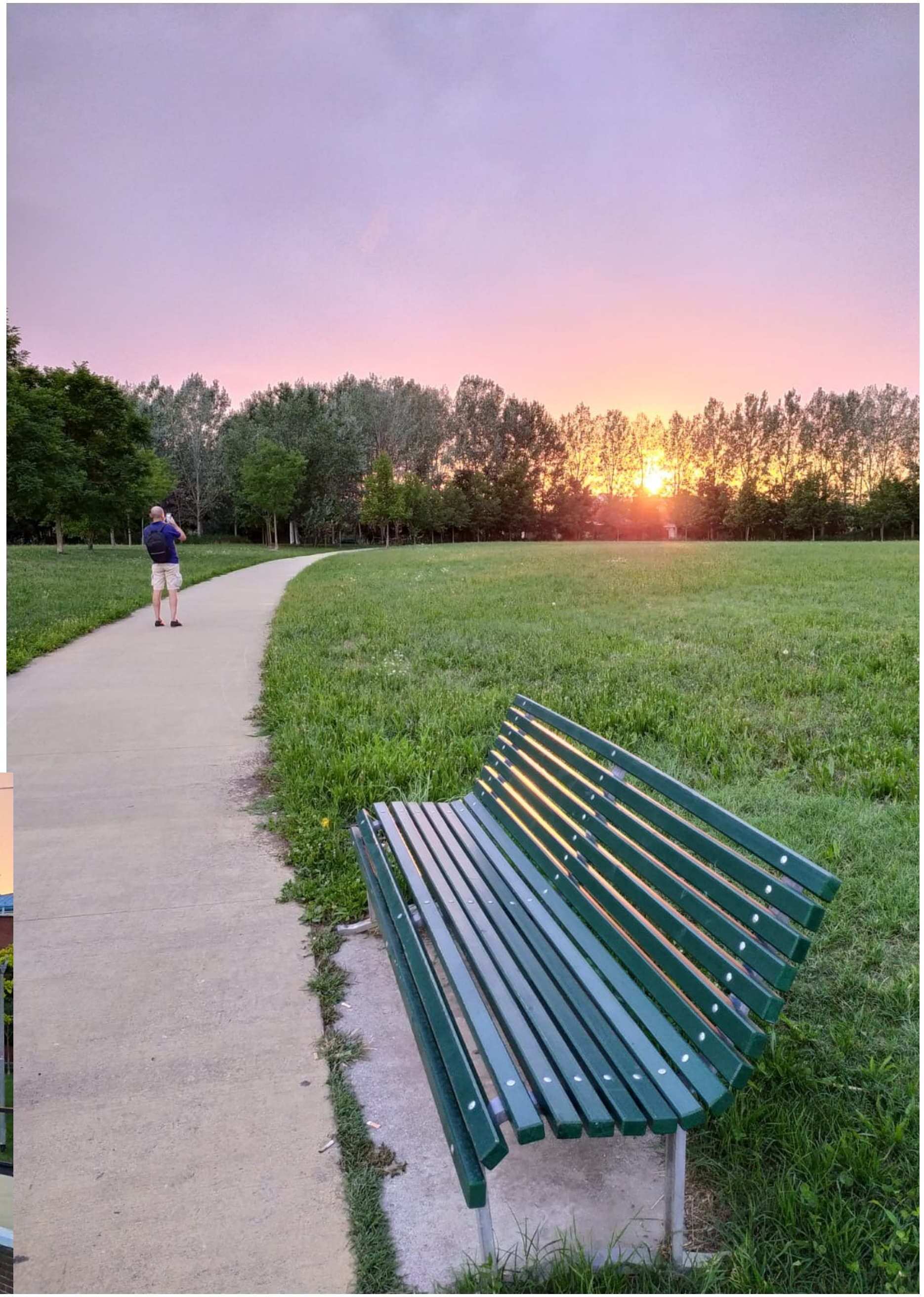
The First cluster is larger than the other two, representing 39.8% of the topics discussed in the reviews regarding the perceived qualities of the physical attributes of the parks and gardens. Where words like

‘beautiful’, ‘nice’, ‘well’, ‘green’, ‘many’, ‘people’, ‘plant’, ‘tree’

describes positive aesthetics.

Words like - ’little’, ‘dirty’, ‘bad’, ‘small’, ‘could’, ‘care’, ‘maintain’, ‘better’, ‘unfortunately’

infer aesthetic and utility reservations that render dissatisfactions to the visitors or those attributes that deter the parks and garden use.



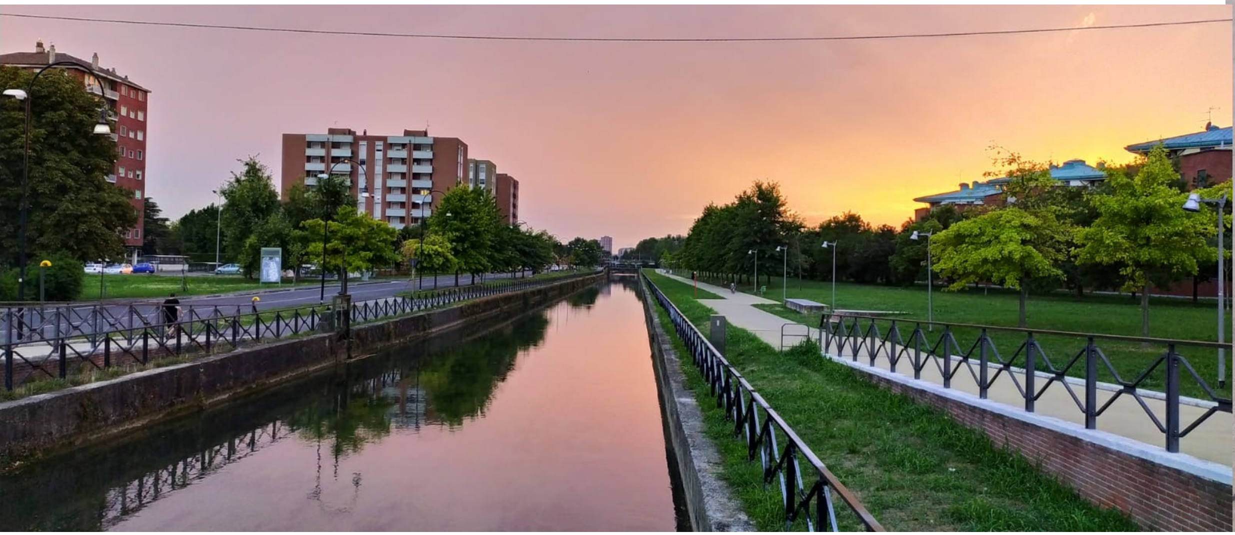
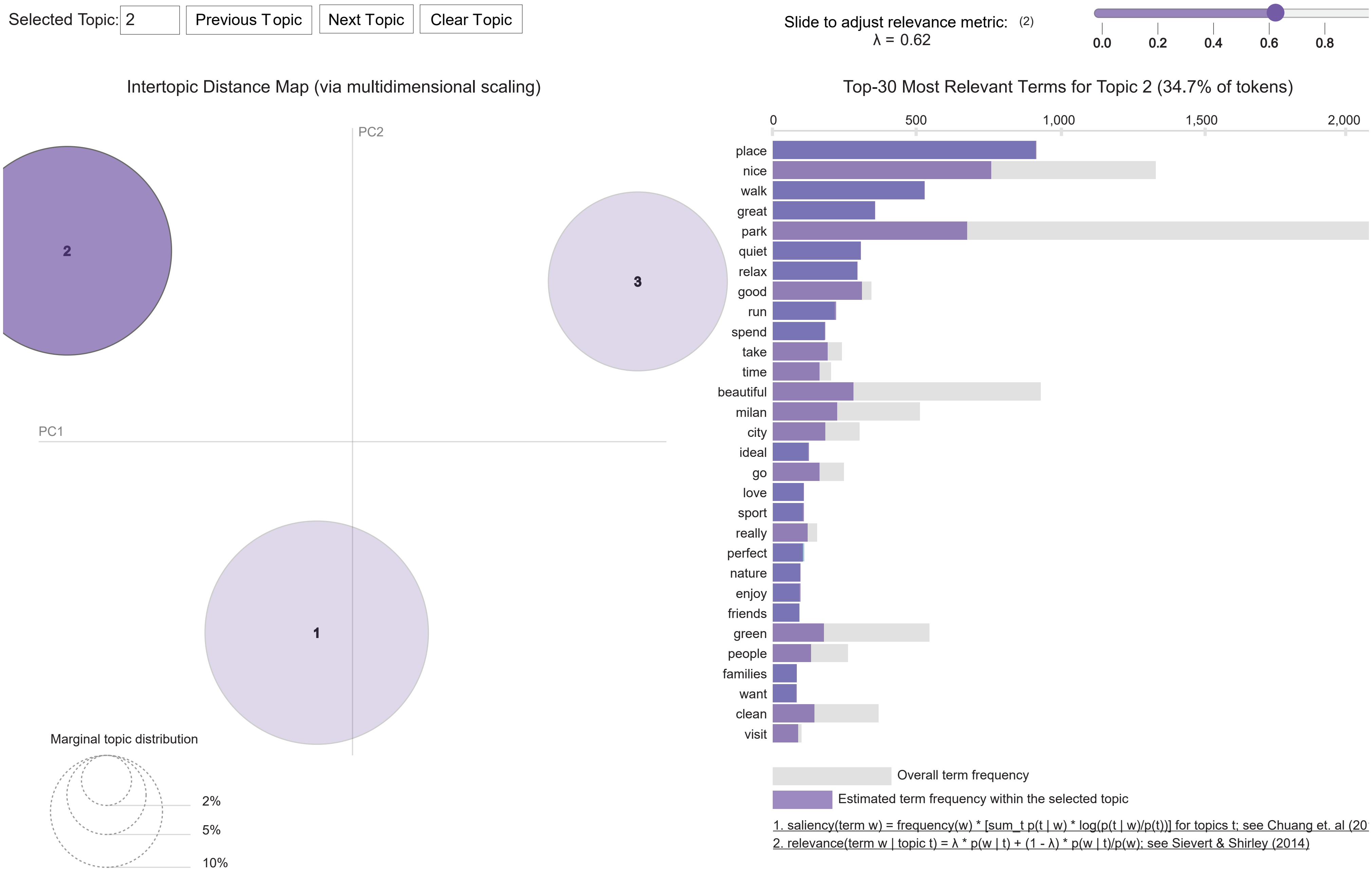


Fig.29.Topic modelling- Model 2- Activites associated parks of the parks and gardens usability :



The second topic is the second most discussed up to 34.7% composed of both the prescriptive and descriptive activities associated with park and garden usability.

‘nice’, ‘place’, ‘walk’,
’quiet’, ‘relax’,
‘good’, ‘run’,
‘spend’, ‘time’,
‘ideal’, ‘go’, ‘love’, ‘sport’,
‘perfect’, ‘nature’,
‘enjoy’, ‘green’, ‘friends’, ‘families’,

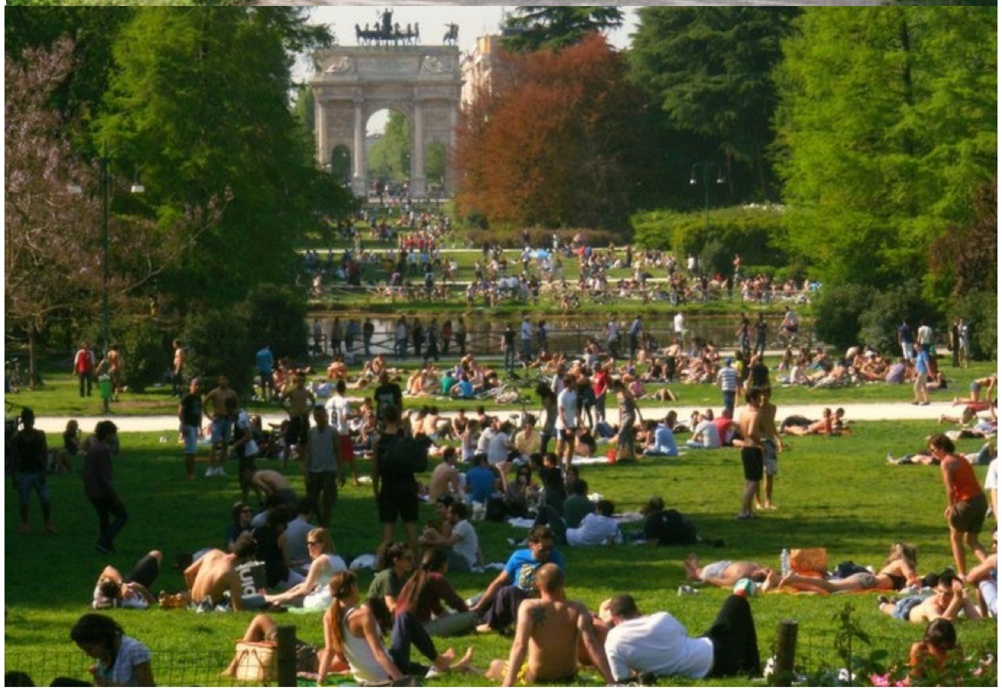
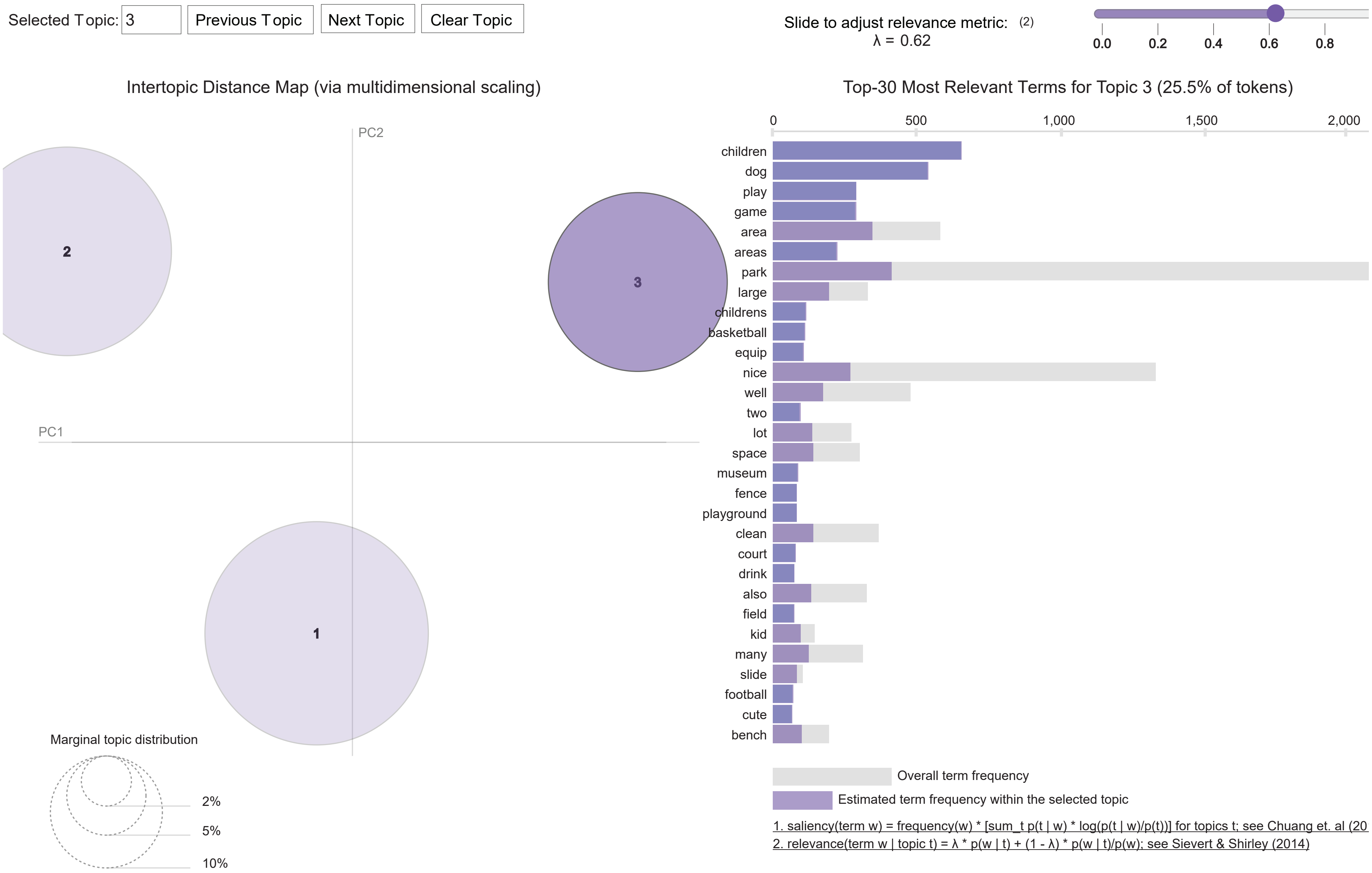


Fig.30. Topic modelling- Model 3- Description of Children and dog areas of the parks and gardens :

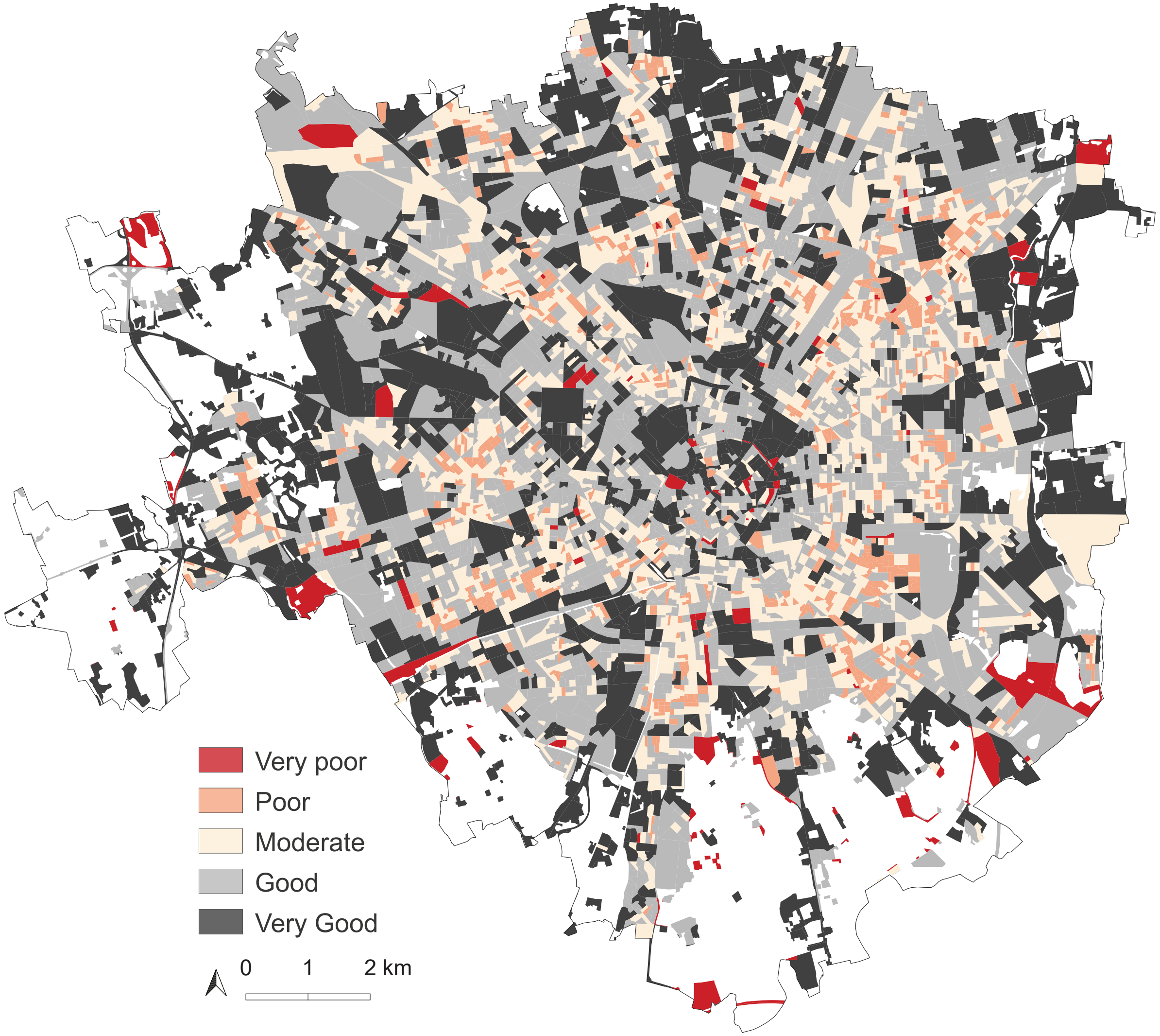


The third topic accounting for 25.5% of the topics discussed in the reviews, describes the perceived qualities of the children and dog play areas of the parks, is composed of words that describe the qualities of activities and equipment.

‘play’,’ game’, ‘basketball’, ’play-ground’, ’court’, ’football’, ‘fields’, ’slide’, ’bench’, ‘fence’, equip’, ‘nice’, ‘area’, ‘space’, ‘clean’, ‘drink’

5.12.Environment Quality Index (EQI)- tracing the zones of preliminary intervention :

Map.29 .Environmental Quality Index (EQI):

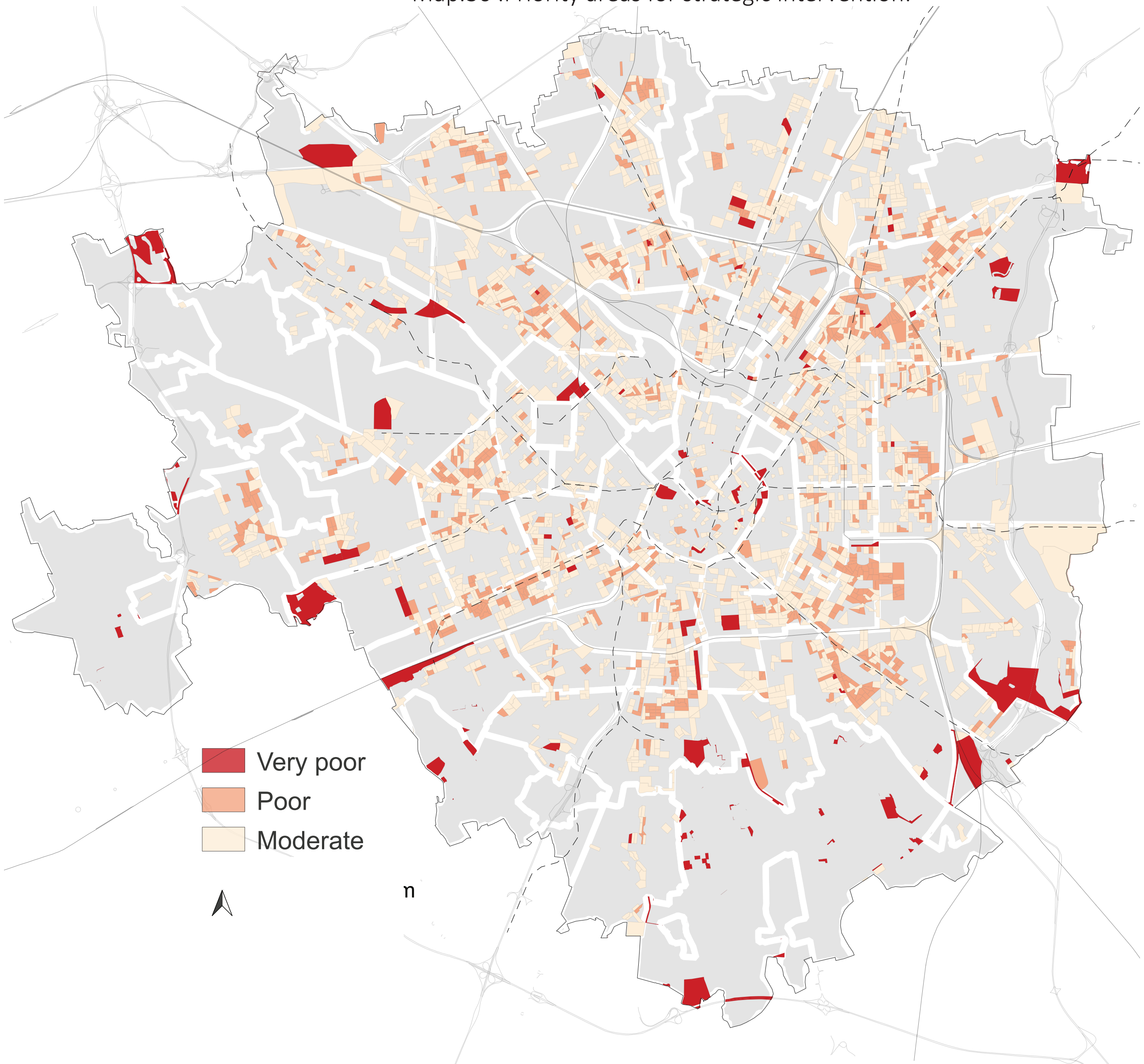


EQI =- PD-HD+NDVI+NDWI-LST-MNDBI+BEER+UFD+R.P.Val+Polarity_of_Gmap_reviews

The EQI Environmental Quality Index delineates the areas concerning levels dereioration and amelioration, excluding the agricultural areas.

5.13. Potentials and Limitations of the framework :

Map.30 .Priority areas for strategic intervention:



Limitations:

- This framework of this study is not an all-encompassed composition of indicators that contribute to environment quality assessment but the methodology is flexible for further incorporations.

- The temporality of the variables date back to past 10 years in case of the census data, where the current scenarios may be different, however embedding the entire framework of this analysis within the temporal cycle of census assessments could enrich the analysis and lead to a cycle of informed policy inputs.

- The incompleteness of data where it concerns the lack of geo-locations of APE certifications sets back the inferences obtained.

- It is imperative to note from the methodology of this social media analysis that from the reviews extracted from google maps the textual reviews posted account for only approximately about 50%, the rest are non-textual numeric ratings. Visitors may perceive a numeric qualification simpler and more impersonal.

- Google maps accumulates the data through a notification prompting feedback of places recently visited, in our smartphone as soon as it has access to a data network and it is purely the subjective motivation of an individual to share their experiential knowledge and opinion on a social platform. This may vary depending on how socially expressive individuals are.

- Smartphone usage in Italy according to statista was around 55% in 2021 and projected to reach around 70% in 2025, as this study was conducted in 2022 retrospecting on the reviews that go back as far as 3 years. This sets limitation of digitation gap is realizing the full application of this methodology.

- The question of privacy and public reliability is key concern which requires confident public-people dynamics.

- 'TextBlob' is a basic text classifier its accuracy in classifying negative polarity is low when compared to more advanced ' Valance Aware Dictionary and Sentiment Reasoner (VADER)' , 'spaCY' or 'Tensorflow'.For example sentences like 'it is not the best' and 'it is not the best' both have positive polarity assigned as the TextBlob pluginin the second sentence does not associate 'not' to 'best' due to pre presence of 'the' and this precisely has altercations on the accuracy.

- Finally, the scale of the analysis limits its potential of procuring intuitive assessments to the nuances of urban growth of Milan. Milan's governance and planning regulations are trans-scalar with the municipal, metropolitan area and regional level interventions mostly run parallel. The analysis focused at the meso- scale fails to capture the spatial scenarios of the results at the metropolitan scale.

Potentials:

- The framework proposed in this study could also be employed in the inter-urban appraisals as a ranking list of urban regions with the most or least environmental quality areas. Either as number of blocks as units of assessment or as the area ratio.

- The Google map reviews data is publicly available, ease in accessibility and source of user-generated data,

- Which is cost effective, efficient data collection and interpretation methodology can save time, money and energy resources to obtained the same from traditional biased inquiries spanning across local contextual thematic streams for an all-encompassed decision-making.

- Social media platforms can be used to attract public-people participation understand people's perceptions sentiments on specific topics, their popularity, develop uniquely designed grassroots solutions through better-informed decisions, policies and strategies implementation in the field of urban and regional planning.

- Understanding and identifying the social dynamics of online community clusters and its users, it is also possible to incite opinion and bring about behavioral change.(López-Ornelas, Abascal-Mena and Zepeda-Hernández, 2017)

- Further streams of study could be the qualification of other tourist attractions to understand, maintain, improve and innovate the experiences of tourism industry or understand the socio- spatial dynamics and satisfaction of housing in the view of different age, income or racial groups.

6. Conclusions and implications…

6.Conclusions and future Implications :

This investigative study attempts to analyze the environmental quality of the city of Milan with respect to the socio-economic, ecological and bio-physical altercation implied by the anthropogenic pursuits of economic competence. Also, the framework of this study in unique in the aspect that it is a first of its kind to utilize social media data analytics in the derivation of a composite index. The overall Index present areas implied according to their environmental quality from being very poor to very good in Map.29. As demonstrated in Map.30 the number of areas in the poorer spectrum is fairly low including built-up and open spaces.

However, the areas classified by moderate environmental qualities are centered around poor qualities one that have to be monitored for further deterioration or analyzed in conjunction with other policy intervention. From the indicator oriented analysis we could infer the spatial homogenous distribution of population densities in the central and semi-central urban areas, while in the peripheral and suburban areas exhibit heterogenous distribution. The household densities also follow a similar trend. As of the current socio-economic standing when compared with other cities of similar size the densities in Milan are lower, although it should be noted that the scenarios at the metropolitan level comparison inference may vary. The urban vegetative cover deteriorates from the center to the peripheries and consequently surface temperature ¬experience inversely diffuse towards the peripheries.

The evaluations of the remotely sensed indices in assessing the intensity of urbanized and building areas lead to conclude that Analyzing the energy efficiency performance of buildings through their acquired energy (APE) certification demonstrated the necessity to motive better performance conformity. However, in the wake of the new fiscal concessions attributed to elevating the performance household fixtures and equipment in the past year may hopefully, reflect alternate inferences. The results of the Building Energy Efficiency Rating index (BEER) that classifies the overall energy performances within the census block could be utilized as a social reporting conduit to encourage neighborhood competitiveness inciting ground behavioral change. Although the lack of completeness of the dataset on geo-spatial location of higher efficiency may modulate the overall index scoring of BEER rating may be a shortcoming. Functional diversity dissemination beyond the central core of Milan has been identified as a drawback that hinders the full economic competence realization which is reflected in the overall Urban Functional diversity Score at 35%. Employing the block-wise result of this data analyzed at the municipal zonal or neighborhood level may aid in co-creation of localized land-use requisites thus, ensuring sociological vitality.

The residential property valuations confirm the conjecture of creative class speculations, this is precisely where the drawback of this analysis restrict from a cohesive interpretation of socio-economic spatial dynamics which may have rendered intuitive directionality to the extent of this trend. However, a scaled-up analysis incorporated with the evaluation of the richness of functional diversity may yield potential test beds for pilot interventions.

To understand civic expectational requirement of urban public space in Milan we choose Google Map reviews for its availability of data as compared with other micro-blogging social media, extracted using python Selenium. Our initial analysis of the parks and garden areas interpretative of its use popularity indicated from the total number of reviews on the platform and their overall functional satisfaction from the star rating incurred illustrates that the most visited park does not necessarily reflect that the people's satisfaction expectational were met. Of course, the data for this inference is layered with large temporal data accumulation of much older reviews. Thus, our approach was to evaluate the most relevant textual review on the platform posted as far four years ago. Preliminary inference was that significant number of people preferred star rating their reviews to textual one reducing the data worked on in the succeeding steps. With the objective to draw insights into the public expectation of open spaces from their textual review a polarity and subjectivity analysis on the text of the reviews was performed using TextBlob in python.

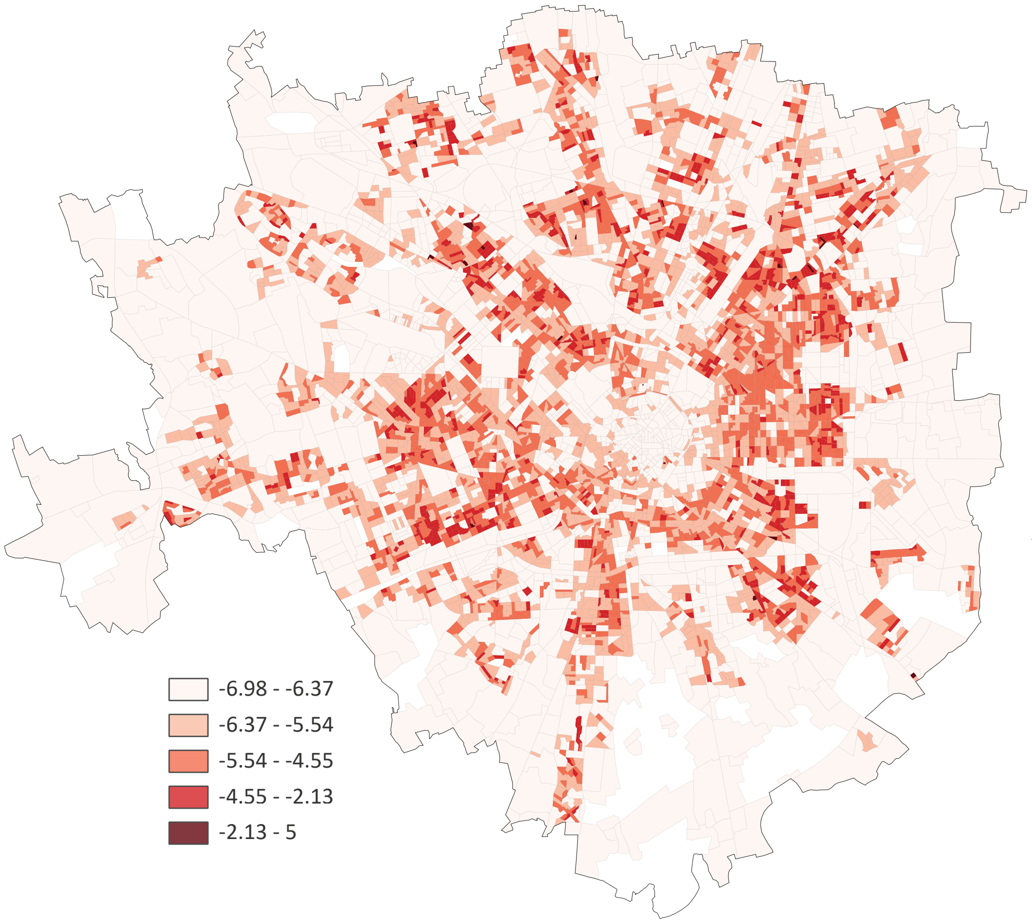
The polarity of sentiments ranks Milan's parks and gardens to be fairly neutral satisfactory levels with no spatial correlation that may attribute the polarity of emotions due to factor external to the parks and garden. Complemented with the subjectivity analysis we could confirm that the sentiments are not garnered as individual personalization but are in-turn associated with the objective experience of the park and garden spaces. Delving deeper into the aspect of the parks and garden that attained popularity of discourse on the social platform topic modelling based on Latent Dirichlet Allocation (LDA) was performed. The result is the identification of the topics based on

1. the physical aesthetic and maintenance attributes of the parks and gardens,
2. opportunities associate with park and garden usability about the activities that are or could be carried on.
3. And finally, describing the physicality of the specific areas of parks and gardens dedicated for children and dogs.

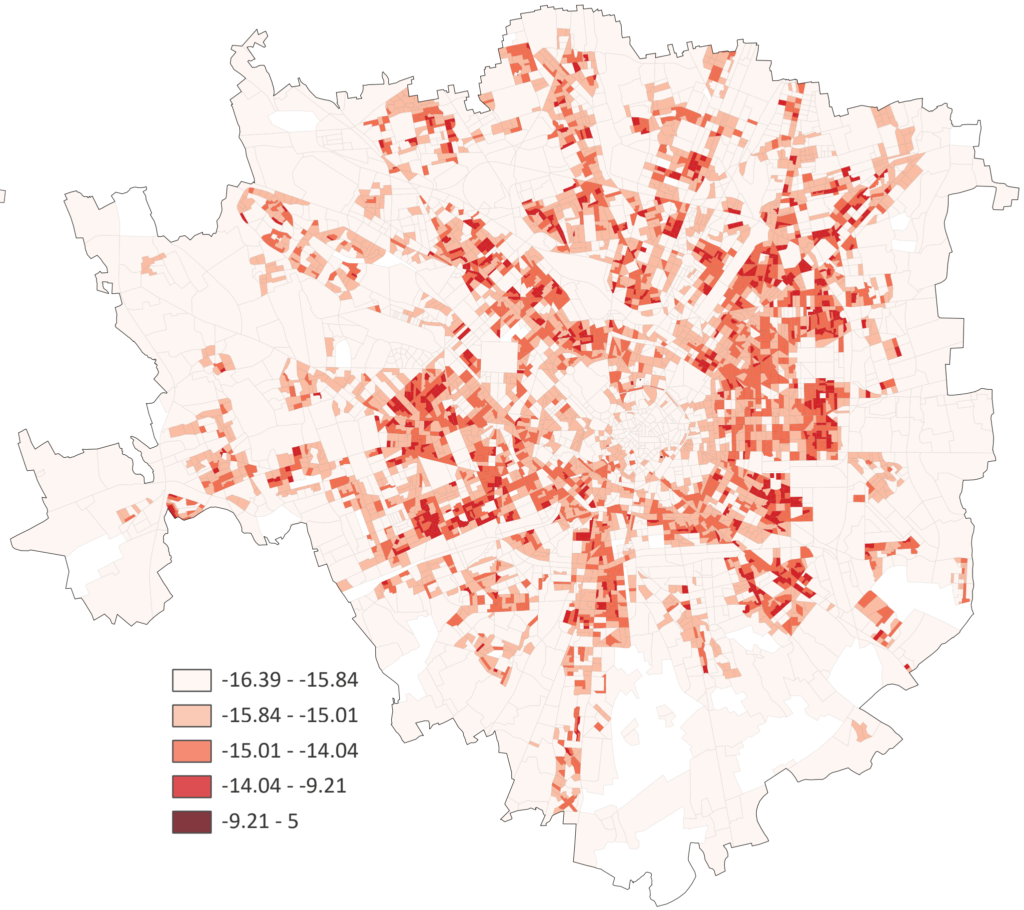
Milan's urban planning envisions strategic interventions through usage of 'urban metaphors' like 'open streets' and 'Citta 20' as conceptual blueprints embed with meanings and social conscious driven strategies. Among the many grassroots co-conceived pilot project realization of the urban public space ecology the results of topic modelling of urban parks and gardens on ¬ Google Map reviews could render broader discourse on the diversification of public space functions embedded with an identity uniqueness and compositional coherence. Social media-based analytics could be expanded to gauge public perceptions and inputs on various urban policies along the socio- spatial context. For instance, tourism behavior opportunities can be improved or explored for potential reinvention of experiences, socio-spatial requirements of diverse age groups, income classes and racial agglomeration can be traced to bring about social liveliness and excitement.

7.1. Ranks

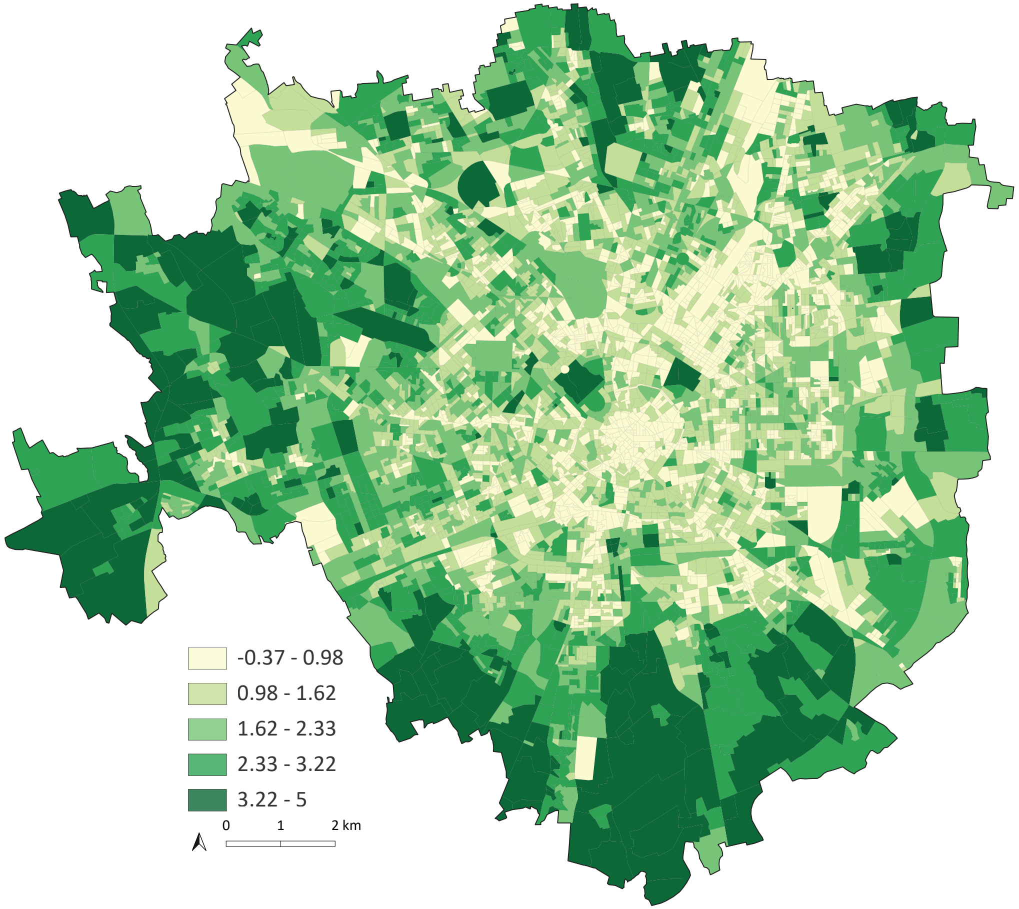
Map.31 . Rank-Population Density (PD):



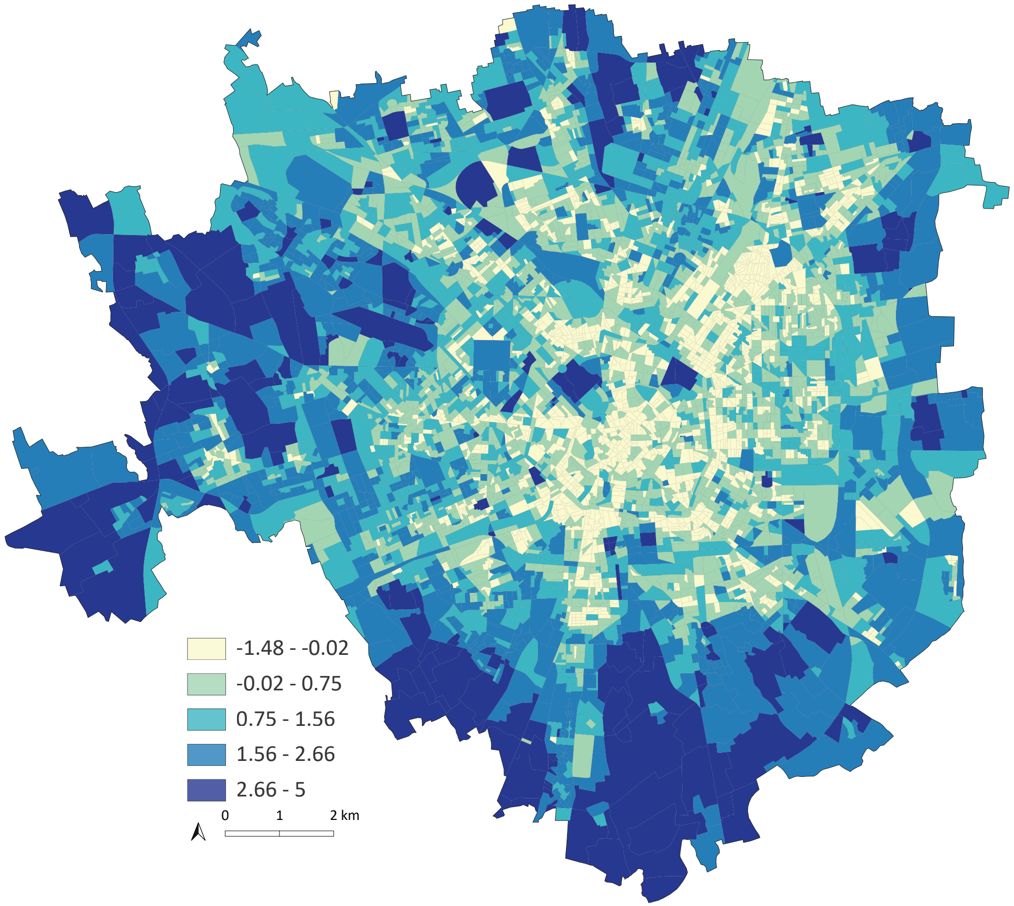
Map.32 .Rank Househols Density (HD) :



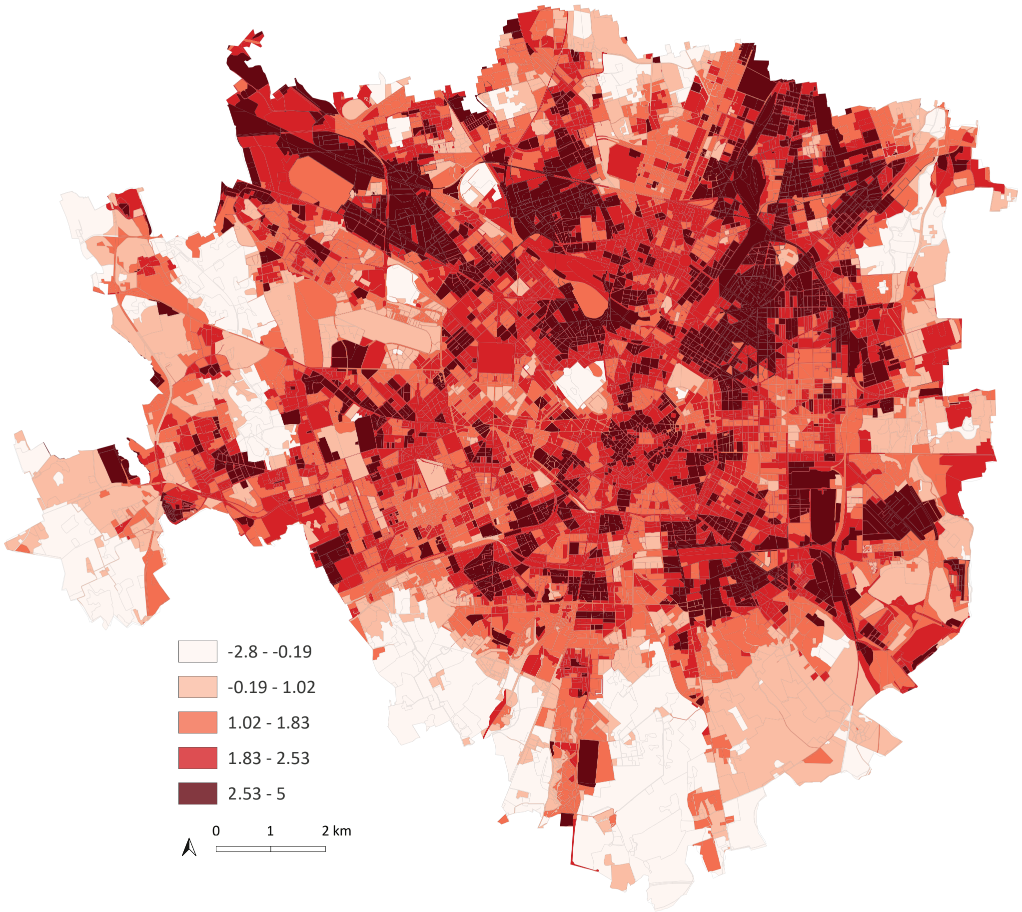
Map.33 .Rank - Normalized Difference Vegetation Index(NDVI) :



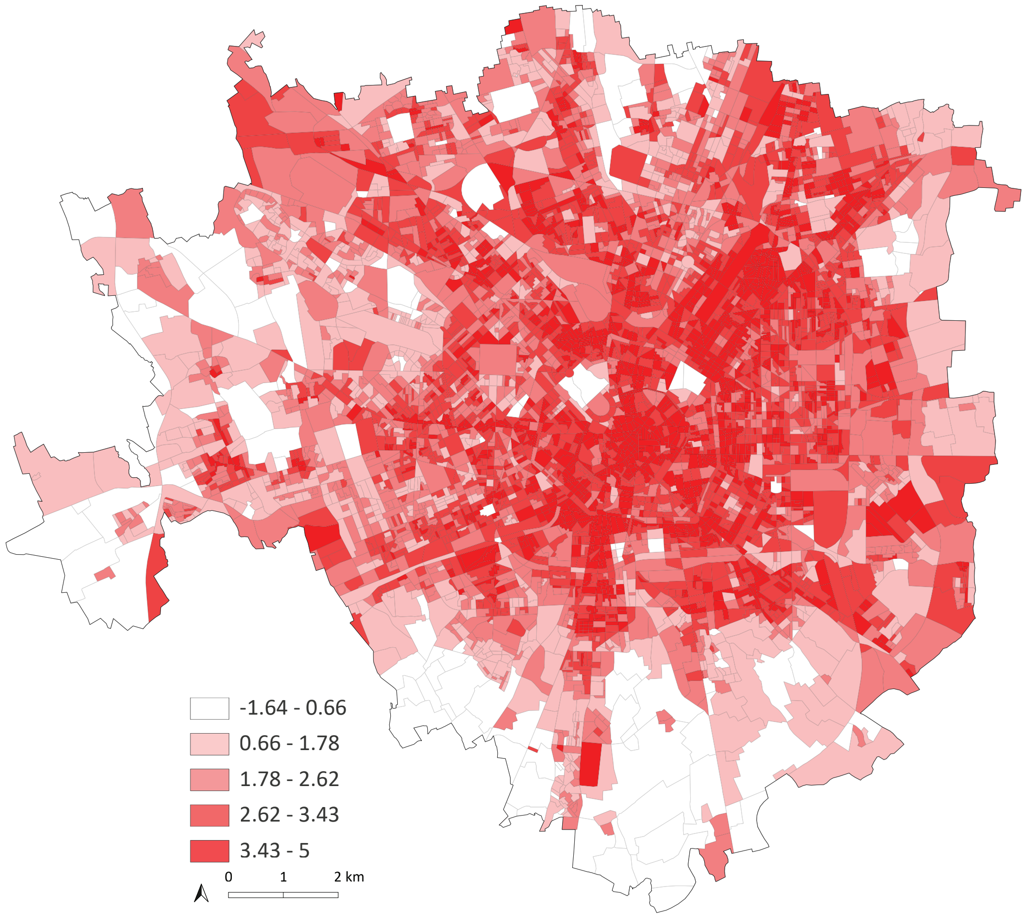
Map.34 .Rank - Normalized Difference Water Index(NDWI) :



Map.35 .Rank- Land Surface Temperature (LST) :

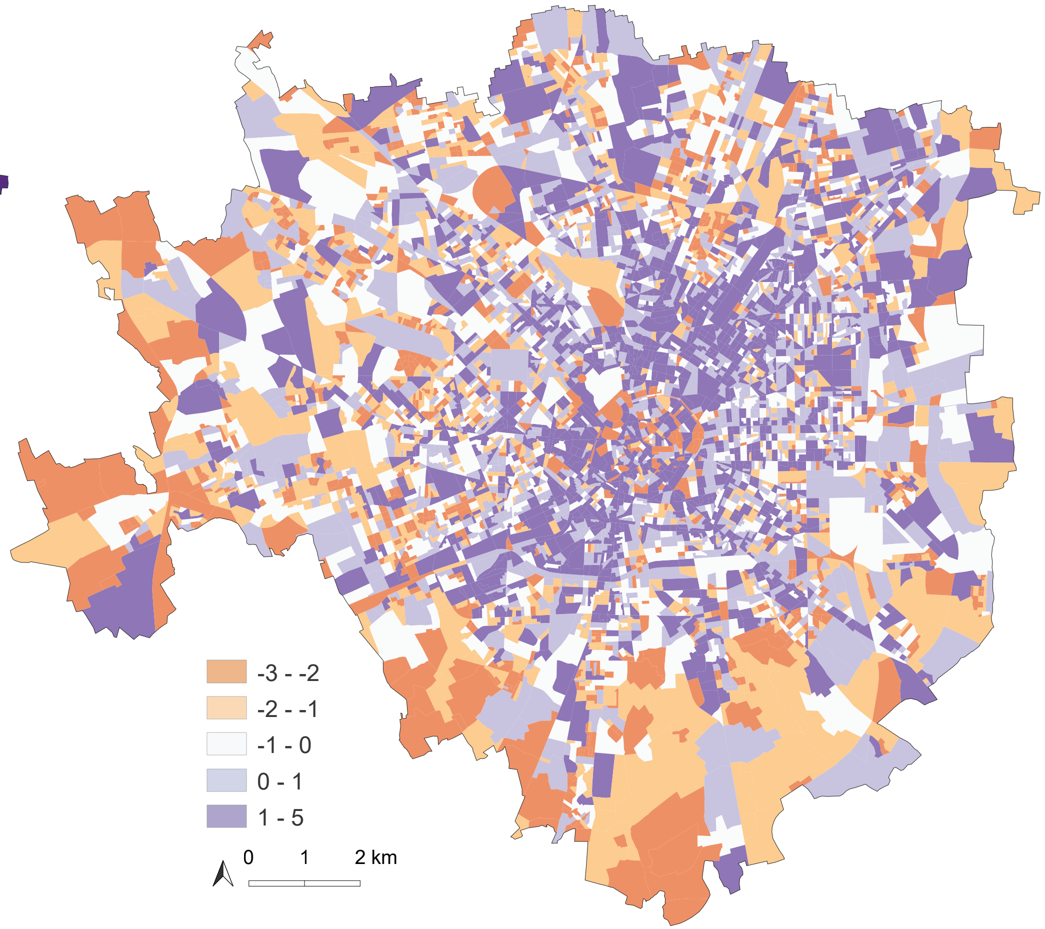


Map.36 . Rank- Modified Difference Built-up Index (MNDBI) :

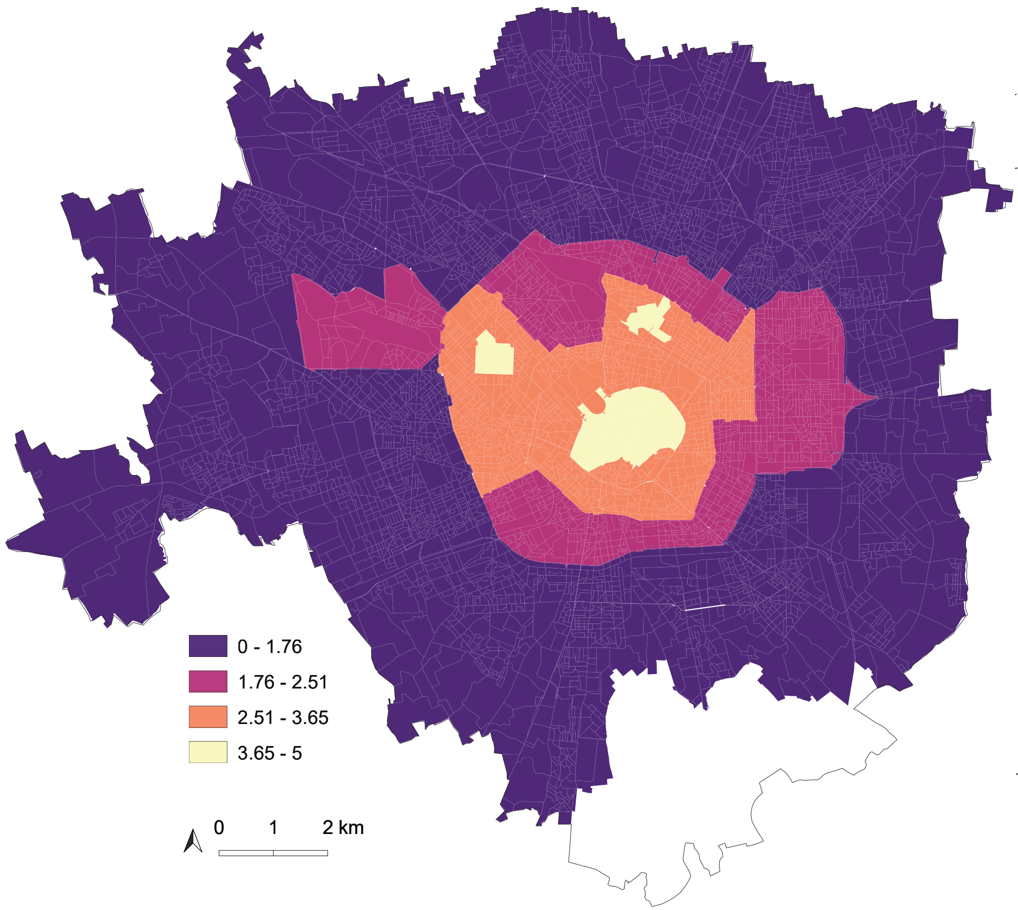


Map.37 .Rank- Building Energy Efficiency Rating :

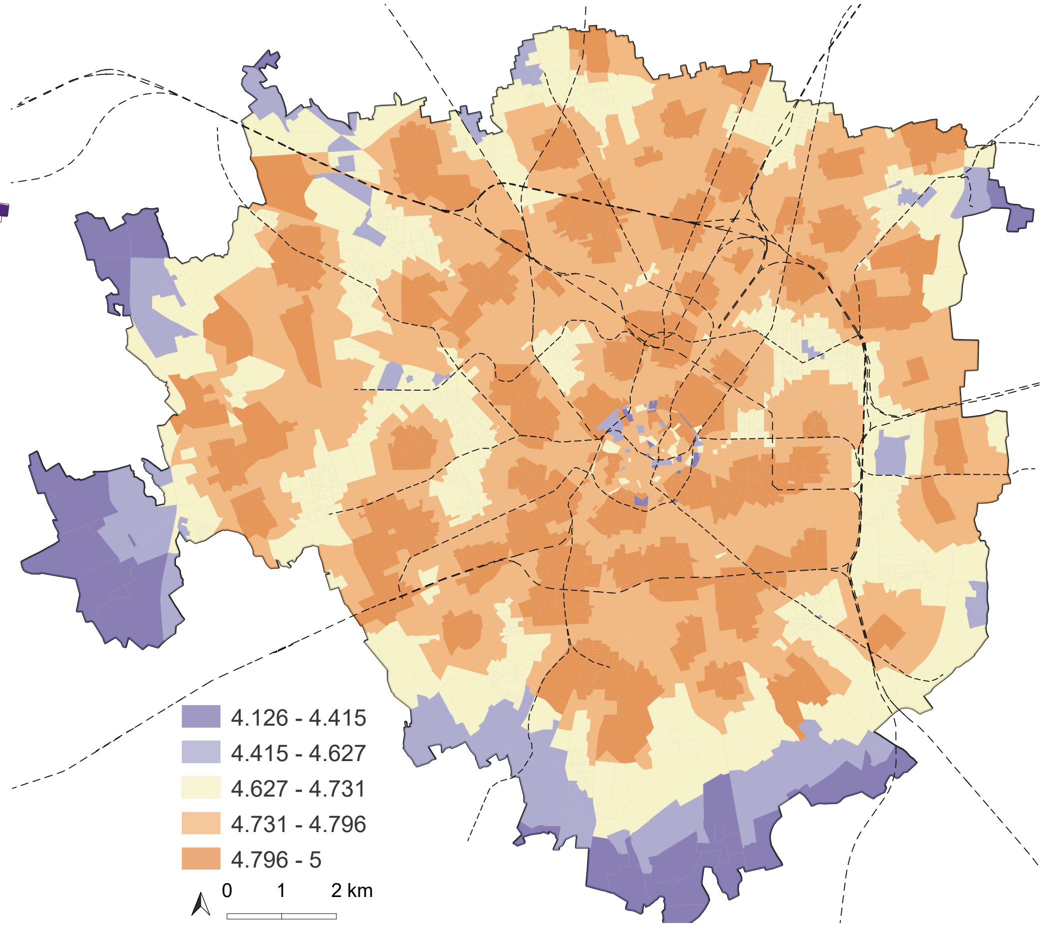
Map.38 .Richness of Functional :



Map.39 .Rank- Residential Property Value (R.P.Val) :



Map.40 .Rank- Polarity of Google Map reviews :



7.2. List of Parks and Gardens analyzed:

Park and Garden Names	rating	total_ratings	avg_polarity	median_ polarity	avg_subjectivity	median_ subjectivity	nos_of_re-views_analyzed	latitude	longitude
North Park of Milan	4.5	1,020 reviews	0.10	0.08	0.19	0.16	116	45.5339604	9.1756289
North Park of Milan	4.5	1,032 reviews	0.10	0.09	0.19	0.17	155	45.53504701	9.175730523
Parco Forlanini	4.5	1,051 reviews	0.13	0.11	0.20	0.18	120	45.4668943	9.2593533
Parco di Villa Scheibler	4.4	1,077 reviews	0.13	0.10	0.20	0.17	103	45.5156982	9.1332809
Parco Giovanni Paolo II	4.2	1,202 reviews	0.10	0.09	0.21	0.19	111	45.4557788	9.1822257
Franco Verga Park	4.3	1,230 reviews	0.11	0.06	0.20	0.15	118	45.5083026	9.1426571
Parco della Resistenza	4.1	1,294 reviews	0.10	0.07	0.19	0.15	114	45.4469207	9.1835446
Cave Park	4.5	1,952 reviews	0.12	0.07	0.19	0.15	119	45.4675557	9.1006642
Parco Industria Alfa Romeo- Portello	4.4	1,964 reviews	0.15	0.11	0.24	0.18	115	45.4878779	9.1459673
Parco Dei 600	4.1	111 reviews	0.17	0.07	0.30	0.19	39	45.5115002	9.134655
giardino Marisa Bellisario	3.8	115 reviews	0.09	0.09	0.23	0.17	31	45.4898181	9.2380649
Giardino Ezio Lucarelli	4.4	116 reviews	0.13	0.06	0.22	0.15	44	45.489249	9.2466003
Parchetto via Martinetti	4.3	122 reviews	0.14	0.08	0.32	0.21	40	45.4666433	9.132759
Giardino Gina Galeotti Bianchi	4	123 reviews	0.14	0.03	0.28	0.18	28	45.5147606	9.1885987
Giardino pubblico- Aldo Protti	3.5	127 reviews	0.11	0.06	0.25	0.19	44	45.4920219	9.1987906
Parco guardi	3.7	135 reviews	0.05	0.04	0.21	0.15	51	45.4701166	9.2266256
Parco pubblico- Gonin	4	135 reviews	0.13	0.09	0.27	0.19	47	45.4420262	9.1262972
Parco pubblico- Primaticcio/dei Gigli	4	139 reviews	0.14	0.09	0.28	0.17	44	45.4666788	9.1435147
Giardino "Aristide Calderini"	4.2	141 reviews	0.08	0.04	0.20	0.15	57	45.4646984	9.1776896
Parco Sandro Pertini	4.3	143 reviews	0.11	0.06	0.26	0.20	50	45.4958246	9.1075541
Isola Pepe Verde IPV	4.4	155 reviews	0.10	0.05	0.19	0.13	60	45.4861111	9.1872222
Parco Conad	3.8	155 reviews	0.09	0.03	0.23	0.17	62	45.4941566	9.1647372
Via Grazioli Gardens	4	161 reviews	0.15	0.06	0.27	0.17	47	45.5079217	9.1745633
Parco nord Milano- Ingresso viale Su-zzani 280	4.6	167 reviews	0.12	0.07	0.24	0.17	65	45.52871433	9.21020594
Monte Stella	4.5	170 reviews	0.10	0.08	0.17	0.14	90	45.4908839	9.1344428
Parco pubblico- Memorie Industriali	4.3	170 reviews	0.14	0.08	0.23	0.18	69	45.4445138	9.1916687

Parco Conca Fallata	4.4	173 reviews	0.14	0.07	0.27	0.17	56	45.4280998	9.1695401
Park Ca'Granda	4.1	173 reviews	0.11	0.04	0.25	0.19	46	45.5061354	9.1996601
Parco pubblico- Insubria	3.2	181 reviews	0.04	0.00	0.23	0.17	71	45.4544511	9.2201449
Parco Quartiere Le Terrazze	4.5	185 reviews	0.15	0.09	0.25	0.16	67	45.4193605	9.1812457
Giardini Indro Montanelli	4.4	19,582 reviews	0.10	0.09	0.17	0.15	114	45.4744236	9.1993609
Parco in Memoria delle Vittime Italiane nei Gulag	4.1	196 reviews	0.12	0.07	0.25	0.20	69	45.4558258	9.0957785
Giardino della Villa Belgiojoso Bonaparte	4.6	197 reviews	0.14	0.10	0.22	0.18	87	45.4718776	9.1993528
Parco Martiri della LibertÃ Iracheni Vittime del Terrorismo	4.1	2,015 reviews	0.11	0.07	0.19	0.14	115	45.5023602	9.2314886
Parco Don Luigi Giussani	4.1	2,054 reviews	0.15	0.08	0.25	0.16	126	45.4579619	9.1663623
Giardini della Guastalla	4.4	2,104 reviews	0.09	0.06	0.19	0.16	113	45.4601234	9.1972682
BoscoincittÃ	4.5	2,192 reviews	0.11	0.08	0.17	0.14	118	45.485	9.0919444
Parco Nord Milano	4.5	2,372 reviews	0.15	0.10	0.22	0.17	158	45.52866695	9.185055937
Parco Alessandrina Ravizza	4.2	2,530 reviews	0.12	0.09	0.21	0.17	110	45.4475876	9.1925712
Parco Trotter	4.1	2,586 reviews	0.14	0.09	0.26	0.20	114	45.4941799	9.2242792
Vittorio Formentano Park	4.2	2,620 reviews	0.17	0.10	0.26	0.19	104	45.4607588	9.2154714
Giardino pubblico - Anna Del Bo Boffino	4.2	210 reviews	0.08	0.05	0.19	0.17	76	45.4483545	9.1512982
Area giochi- Dezza	3.9	212 reviews	0.10	0.05	0.21	0.13	64	45.4617182	9.1596001
Lambretta Park	4	216 reviews	0.10	0.05	0.24	0.16	81	45.480149	9.2515407
Parco Wanda Osiris	4	216 reviews	0.13	0.08	0.26	0.19	74	45.5025595	9.1953809
Park formerly Armenia Films	4.3	216 reviews	0.11	0.07	0.26	0.21	73	45.5044151	9.1713711
parco del Fanciullo	4.2	217 reviews	0.08	0.02	0.20	0.14	68	45.475235	9.1071646
Francesco di Cataldo Park	4	266 reviews	0.09	0.06	0.21	0.15	86	45.5135777	9.2328426
Parco Nord Milano	4.6	269 reviews	0.20	0.13	0.30	0.21	103	45.53102532	9.198763822
Gardens "Falcone e Borsellino"	4	282 reviews	0.10	0.05	0.24	0.17	96	45.4793184	9.2064976
Parco La Spezia	4.2	297 reviews	0.13	0.06	0.25	0.17	103	45.4405474	9.1696571
Parco Nord Milano	4.5	3,123 reviews	0.11	0.08	0.20	0.16	153	45.53532909	9.213388445
parco Aldo Aniasi	4.4	3,330 reviews	0.12	0.07	0.17	0.14	114	45.4863185	9.1070067

Parco Biblioteca degli Alberi	4.6	3,381 reviews	0.20	0.15	0.27	0.20	119	45.4843239	9.1923138
Acquatica Park	4	3,668 reviews	0.17	0.09	0.30	0.20	112	45.4725634	9.0812878
Parco Nord Milano	4.7	302 reviews	0.16	0.11	0.23	0.19	101	45.54189828	9.210010498
Parco pubblico- Cascina Merlata	4.4	331 reviews	0.16	0.11	0.27	0.21	117	45.511314	9.1032149
Parco della Vettabbia	4.4	344 reviews	0.12	0.10	0.20	0.17	117	45.4284554	9.2231989
Pompeo Castelli Public Garden	3.5	353 reviews	0.06	0.00	0.19	0.13	102	45.499147	9.1510771
Parco Guido Vergani	4.1	364 reviews	0.12	0.08	0.24	0.17	109	45.4706656	9.1613854
Giardino pubblico- Cassina de Pomm	4.2	365 reviews	0.09	0.03	0.20	0.16	113	45.4971286	9.2090387
Parco Adriano	4.4	372 reviews	0.15	0.12	0.25	0.19	115	45.5175987	9.2536876
Giardini Perego	4.4	379 reviews	0.08	0.05	0.23	0.18	120	45.4721623	9.1927088
Garden of Red Cross nurses	4	396 reviews	0.12	0.08	0.22	0.18	107	45.4499239	9.123842
Community Garden Lea Garofalo	4.3	398 reviews	0.11	0.06	0.20	0.18	115	45.48098	9.1817111
Agricultural Ticinello Park	4.4	405 reviews	0.11	0.08	0.18	0.16	116	45.4275149	9.1821997
Giardino Alberto Moravia	4	414 reviews	0.12	0.06	0.22	0.17	107	45.4562189	9.1256515
Parco nord milano	4.6	467 reviews	0.13	0.10	0.22	0.18	154	45.54197344	9.197860485
parco MonluÃ¨	4.2	479 reviews	0.10	0.07	0.20	0.16	114	45.4570626	9.255879
Giardino Marcello Candia	4.1	493 reviews	0.09	0.06	0.21	0.19	114	45.4467646	9.2147834
Parco Lambro	4.2	5,030 reviews	0.13	0.11	0.19	0.17	113	45.4957003	9.2487516
Giardino Balduccio da Pisa/Calabiana	3.6	51 reviews	0.13	0.07	0.23	0.20	22	45.4424747	9.2084202
Parco Argelati	4.2	51 reviews	0.10	0.04	0.20	0.13	14	45.44761145	9.1697176
Giardino delle Culture	4.2	538 reviews	0.08	0.07	0.17	0.15	108	45.4611188	9.2111094
Parco pubblico- Coari	3.7	54 reviews	0.13	0.05	0.30	0.17	13	45.435042	9.1978197
Giardino Mauro Capponi	3.8	56 reviews	0.07	0.02	0.20	0.14	18	45.4406408	9.185609
Parco Nord	3.9	56 reviews	0.11	0.15	0.39	0.36	12	45.64919478	8.905958227
Giardini Maria Peron e Suor Giovanna Mosna	4.1	57 reviews	0.10	0.06	0.20	0.17	16	45.5207431	9.1958498
Giardino Roberto Bazlen e Luciano FoÃ	3.8	60 reviews	0.04	0.02	0.15	0.15	23	45.4549755	9.197202
Sempione Park	4.6	60,632 reviews	0.10	0.09	0.16	0.15	114	45.4720981	9.1772243
Parco di Baggio	4.1	601 reviews	0.11	0.08	0.19	0.16	116	45.4638826	9.0897296

Parco pubblico- Candiani	3.8	61 reviews	0.08	0.05	0.16	0.14	15	45.506235	9.1729211
Giovanni Testori Park	4	623 reviews	0.07	0.05	0.17	0.14	227	45.4988252	9.1546255
Parco Vittoria	4.3	63 reviews	0.09	0.02	0.23	0.15	19	45.4538239	9.15570325
Giardino Laura Conti	3.8	64 reviews	0.16	0.18	0.37	0.33	21	45.4942188	9.1503956
Giardino Oreste del Buono	4.1	644 reviews	0.08	0.06	0.19	0.18	112	45.4634618	9.2248956
Collina dei Ciliegi	4.3	650 reviews	0.12	0.09	0.20	0.17	119	45.5088419	9.17437175
Parco Segantini	4.2	669 reviews	0.11	0.08	0.20	0.19	113	45.4465158	9.1710628
Parco NicolÃ² Savarino	4	676 reviews	0.08	0.05	0.20	0.14	112	45.4994924	9.1772846
Parco pubblico - Marco d'Agrate/Ortles	3.6	68 reviews	0.07	0.05	0.16	0.13	31	45.4383746	9.2090786
Shared Garden	4.2	68 reviews	0.06	0.05	0.18	0.14	34	45.47810655	9.18044305
Parco Nord Milano- Area Teatrino	4.4	688 reviews	0.13	0.10	0.21	0.17	158	45.53056689	9.210736569
Parco pubblico- Cascina Caimera	4.2	69 reviews	0.15	0.12	0.26	0.17	25	45.4298008	9.1705581
Parco delle Cascine di Chiesa Rossa	4.4	701 reviews	0.10	0.08	0.19	0.16	119	45.4312629	9.1742783
Giardino 9 Novembre	3.9	72 reviews	0.11	0.05	0.31	0.20	29	45.4583367	9.2056157
Giardino Silvio Federico Baridon (giÃ Parco Franco Russoli)	4.2	74 reviews	0.19	0.13	0.35	0.21	28	45.441311	9.1646592
Parco Emilio Alessandrini	3.9	747 reviews	0.10	0.07	0.23	0.20	115	45.4496875	9.2262885
Parco pubblico- Giovannino Guareschi	4	77 reviews	0.13	0.06	0.23	0.12	21	45.4282235	9.2051344
Parco Trapezio Santa Giulia	4.2	773 reviews	0.06	0.05	0.16	0.14	110	45.4359443	9.2423194
parco di Villa Finzi	4.1	782 reviews	0.08	0.05	0.20	0.17	117	45.5053356	9.2199755
Robert Baden-Powell Park	4.2	787 reviews	0.12	0.09	0.21	0.19	120	45.4483081	9.1674001
Parco Nord Milano - Cinisello Sede Cascina	4.6	791 reviews	0.11	0.08	0.18	0.14	154	45.53799519	9.20937144
Parco Andrea Campagna	4.3	812 reviews	0.10	0.06	0.18	0.14	114	45.4362254	9.1436077
Parco pubblico- Savona/Brunelleschi	4.1	82 reviews	0.10	0.06	0.25	0.15	30	44.74014355	8.62006665
Parco di Villa Litta	4.5	850 reviews	0.11	0.08	0.19	0.17	120	45.515954	9.1671751
Giardino dei Giusti di tutto il Mondo	4.5	92 reviews	0.12	0.04	0.17	0.08	37	45.4894076	9.1364233
CityLife Park	4.5	942 reviews	0.14	0.08	0.22	0.17	113	45.4766466	9.156154
Parco pubblico- Cesare Pagani	3.6	95 reviews	0.18	0.05	0.36	0.24	29	45.5040152	9.1778691
San Romano Park	4	97 reviews	0.16	0.13	0.32	0.25	28	45.4989523	9.1056822
Giardini Bazzega-Padovani	4	98 reviews	0.12	0.06	0.30	0.18	37	45.4531271	9.1589291

7.3.Code

Code for Phase 1 : (Extracting the Parks and Garden list of Milan at the metropolitan city lvl. scale google maps search under the “ City Park” Business category) :

```
from selenium import webdriver

from selenium.webdriver.common.by import By

from selenium.webdriver.support.ui import WebDriverWait
from selenium.webdriver.support import expected_conditions as EC
from selenium.webdriver.common.keys import Keys
from selenium.common.exceptions import NoSuchElementException, TimeoutException, ElementNotInteractableException, ElementClickInterceptedException
from tqdm import tqdm_notebook as tqdmn
import pandas as pd
import numpy as np
import folium
import time, re
driver= webdriver.Chrome('C:\Program Files (x86)\Chromedriver.exe')
driver.implicitly_wait(10)

#Part 1

url = 'https://www.google.com/maps/search/City+park/@45.4626268,9.1076922,12z/data=!3m1!4b1!4m2!2m1!6e1'
driver.get(url)
Parks = []
for i in tqdmn(range(9), leave=False, desc ='1.Rounding the competition'):
    element = WebDriverWait(driver,10).until(EC.visibility_of_element_located((By.XPATH,'/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/
div[1]')))

 # Capturing the names and addresses of the competitors and adding them to our list 'competition' :
    result1= driver.find_element_by_xpath('/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[3]/div[1]/div[2]')
    n1=[ driver.find_element_by_xpath('/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[3]/div[1]/div[2]/div[2]/div[1]/div[1]/div[1]/
div[1]/div[1]/div[1]').text]
```

```
    result2= driver.find_element_by_xpath('/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[5]/div[1]/div[2]')
    n2=[ driver.find_element_by_xpath('/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[5]/div[1]/div[2]/div[2]/div[1]/div[1]/div[1]/
div[1]/div[1]/div[1]').text ]

    result3= driver.find_element_by_xpath('/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[7]/div[1]/div[2]')
n3=[driver.find_element_by_xpath('/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[7]/div[1]/div[2]/div[2]/div[1]/div[1]/div[1]/div[1]/
div[1]/div[1]').text ]
    time.sleep(2)

    result4 = driver.find_element_by_xpath('/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[9]/div[1]/div[2]')
    result4.location_once_scrolled_into_view
    time.sleep(2)
    n4=[ driver.find_element_by_xpath('/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[9]/div[1]/div[2]/div[2]/div[1]/div[1]/div[1]/
div[1]/div[1]/div[1]').text]


    result5 = driver.find_element_by_xpath('/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[11]/div[1]/div[2]')
    result5.location_once_scrolled_into_view
    time.sleep(2)
n5=[driver.find_element_by_xpath('/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[11]/div[1]/div[2]/div[2]/div[1]/div[1]/div[1]/
div[1]/div[1]/div[1]').text]

   result6 = driver.find_element_by_xpath('/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[13]/div[1]/div[2]')
    result6.location_once_scrolled_into_view
    time.sleep(2)
n6=[driver.find_element_by_xpath('/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[13]/div[1]/div[2]/div[2]/div[1]/div[1]/div[1]/
div[1]/div[1]/div[1]').text]

    result7 = driver.find_element_by_xpath('/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[15]/div[1]/div[2]')
    result7.location_once_scrolled_into_view
    time.sleep(2)
n7=[driver.find_element_by_xpath('/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[15]/div[1]/div[2]/div[2]/div[1]/div[1]/div[1]/
div[1]/div[1]/div[1]').text]

    result8 = driver.find_element_by_xpath('/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[17]/div[1]/div[2]')
```

```
result8.location_once_scrolled_into_view
time.sleep(2) n8=[driver.find_element_by_xpath(‘/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[17]/div[1]/div[2]/div[2]/div[1]/
div[1]/div[1]/div[1]/div[1]/div[1]’).text]

result9= driver.find_element_by_xpath(‘/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[19]/div[1]/div[2]’)
result9.location_once_scrolled_into_view
time.sleep(2)
n9=[driver.find_element_by_xpath(‘/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[19]/div[1]/div[2]/div[2]/div[1]/div[1]/div[1]/
div[1]/div[1]/div[1]’).text]

result10= driver.find_element_by_xpath(‘/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[21]/div[1]/div[2]’)
result10.location_once_scrolled_into_view
time.sleep(2)   n10=[driver.find_element_by_xpath(‘/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[21]/div[1]/div[2]/div[2]/
div[1]/div[1]/div[1]/div[1]/div[1]/div[1]’).text]

result11 = driver.find_element_by_xpath(‘/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[23]/div[1]/div[2]’)
result11.location_once_scrolled_into_view
time.sleep(2)
n11=[driver.find_element_by_xpath(‘/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[23]/div[1]/div[2]/div[2]/div[1]/div[1]/div[1]/
div[1]/div[1]/div[1]’).text]

result12= driver.find_element_by_xpath(‘/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[25]/div[1]/div[2]’)
result12.location_once_scrolled_into_view
time.sleep(2)
n12=[driver.find_element_by_xpath(‘/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[25]/div[1]/div[2]/div[2]/div[1]/div[1]/div[1]/
div[1]/div[1]/div[1]’).text]

result13= driver.find_element_by_xpath(‘/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[27]/div[1]/div[2]’)
result13.location_once_scrolled_into_view
time.sleep(2)
n13=[driver.find_element_by_xpath(‘/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[27]/div[1]/div[2]/div[2]/div[1]/div[1]/div[1]/
div[1]/div[1]/div[1]’).text]

result14= driver.find_element_by_xpath(‘/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[29]/div[1]/div[2]’)
result14.location_once_scrolled_into_view
time.sleep(2)
```

```
n14=[  driver.find_element_by_xpath('/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[29]/div[1]/div[2]/div[2]/div[1]/div[1]/
div[1]/div[1]/div[1]/div[1]').text]


result15= driver.find_element_by_xpath('/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[31]/div[1]/div[2]')
result15.location_once_scrolled_into_view
time.sleep(2)
n15=[driver.find_element_by_xpath('/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[31]/div[1]/div[2]/div[2]/div[1]/div[1]/div[1]/
div[1]/div[1]/div[1]').text]

result16= driver.find_element_by_xpath('/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[33]/div[1]/div[2]')
result16.location_once_scrolled_into_view
time.sleep(2)
n16=[driver.find_element_by_xpath('/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[33]/div[1]/div[2]/div[2]/div[1]/div[1]/div[1]/
div[1]/div[1]/div[1]').text]

result17= driver.find_element_by_xpath('/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[35]/div[1]/div[2]')
result17.location_once_scrolled_into_view
time.sleep(2)
n17=[driver.find_element_by_xpath('/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[35]/div[1]/div[2]/div[2]/div[1]/div[1]/div[1]/
div[1]/div[1]/div[1]').text]

result18= driver.find_element_by_xpath('/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[37]/div[1]/div[2]')
result18.location_once_scrolled_into_view
time.sleep(2)
n18=[driver.find_element_by_xpath('/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[37]/div[1]/div[2]/div[2]/div[1]/div[1]/div[1]/
div[1]/div[1]/div[1]').text]

result19= driver.find_element_by_xpath('/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[39]/div[1]/div[2]')
result19.location_once_scrolled_into_view
time.sleep(2)
n19=[ driver.find_element_by_xpath('/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[39]/div[1]/div[2]/div[2]/div[1]/div[1]/
div[1]/div[1]/div[1]/div[1]').text]

result20= driver.find_element_by_xpath('/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[41]/div[1]/div[2]')
result20.location_once_scrolled_into_view
```

```
    time.sleep(2)
 n20=[driver.find_element_by_xpath('/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/div[1]/div[2]/div[1]/div[41]/div[1]/div[2]/div[2]/div[1]/div[1]/div[1]/
div[1]/div[1]/div[1]').text]

    Parks.append(n1)
    Parks.append(n2)
    Parks.append(n3)
    Parks.append(n4)
    Parks.append(n5)
    Parks.append(n6)
    Parks.append(n7)
    Parks.append(n8)
    Parks.append(n9)
    Parks.append(n10)
    Parks.append(n11)
    Parks.append(n12)
    Parks.append(n13)
    Parks.append(n14)
    Parks.append(n15)
    Parks.append(n16)
    Parks.append(n17)
    Parks.append(n18)
    Parks.append(n19)
    Parks.append(n20)
    print(len(Parks))

 # Waiting for the 'Next' button to be visible and then click it (if it's not clickable, we break the for loop) :
    try :
      Last_elementofpage= WebDriverWait(driver,70).until(EC.visibility_of_element_located((By.XPATH,'/html[1]/body[1]/div[3]/div[9]/div[8]/div[1]/div[1]/div[1]/
div[1]/div[2]/div[1]/div[41]/div[1]/div[2]/div[2]/div[1]/div[1]/div[1]/div[1]/div[1]/div[1]')))
      next_button= WebDriverWait(driver,10).until(EC.visibility_of_element_located((By.XPATH,'//*[@id= "ppdPk-Ej1Yeb-LgbsSe-tJiF1e"]')))
      if Last_elementofpage and next_button:
        next_button.click()
    except ElementClickInterceptedException :
       break
```

```
 # Waiting 5 seconds before looping (otherwise we get the error ElementClickInterceptedException). If you get the exception, make it wait for a little longer than 5 seconds :
        time.sleep(5)
driver.quit()
```

Code for Phase 2- Automating extraction of the finalized list of parks to obtain their nos. of rating, their rating value and their location coordinates:

```
from selenium import webdriver
from selenium.webdriver.common.by import By
from selenium.webdriver.support.ui import WebDriverWait
from selenium.webdriver.support import expected_conditions as EC
from selenium.webdriver.common.keys import Keys
from selenium.common.exceptions import NoSuchElementException, TimeoutException, ElementNotInteractableException, ElementClickInterceptedException
from tqdm import tqdm_notebook as tqdmn
import pandas as pd
import numpy as np
import folium
import time, re
driver= webdriver.Chrome("C:\Program Files (x86)\Chromedriver.exe")
driver.implicitly_wait(15)

import pandas as pd
with open('D:/Thesis/gis&sats file/UFD/Parks/parks.csv', encoding='utf8') as file:
   Parks1 = file.read().splitlines()

# These are the empty lists we will populate with the extracted data in the 2nd phase :
ParksNames=[]
rating = []
total_ratings = []
business_cat = []
hours= []
lat = []
long = []

# Here's the big loop iterating over the competiton list :
for Parks1 in tqdmn(Parks1, leave=False, desc='2. Extracting the data') :
```

```
    # URL making :
    url = 'https://www.google.com/maps/search/' + Parks1 + ''+ '' + ' Metropolitan City of Milan, Italy'
    driver.get(url)

    # Waiting for the name of the business to load and be visible. If it fails, skip to next business in competition list :
    try :
        WebDriverWait(driver,25).until(EC.visibility_of_element_located((By.CLASS_NAME,"x3AX1-LfntMc-header-title-ij8cu")))
    except (NoSuchElementException, TimeoutException) as e :
        continue

    # Extracting the data and putting it into the empty lists we defined earlier :
    try:
        ParksNames.append(driver.find_element_by_xpath('//h1[@class="x3AX1-LfntMc-header-title-title gm2-headline-5"]').text)
    except NoSuchElementException :
        ParksNames.append(np.nan)

    try:
        rating.append(driver.find_element_by_xpath(('//span[@class="aMPvhf-fI6EEc-KVuj8d"]')).text)
    except NoSuchElementException :
        rating.append(np.nan)

    try:
  business_cat.append(driver.find_element_by_xpath('//button[@jsaction="pane.rating.category"]').text)
    except NoSuchElementException:
        business_cat.append(np.nan)
    try:
        tr= driver.find_element_by_xpath("//div[@class='jANrlb']")
        tr.location_once_scrolled_into_view
        time.sleep(2)
        total_ratings.append(driver.find_element_by_xpath("//button[@class='HHrUdb gm2-button-alt HHrUdb-v3pZbf']").text)
    except NoSuchElementException:
        total_ratings.append(np.nan)

   # Here we capture the popular hours for all 7 days starting with Sunday :
    try:
```

```
        hr= driver.find_element_by_xpath("//div[@class='O9Q0Ff-NmME3c-Utye1-Fq92xe O9Q0Ff-NmME3c-Utye1-Fq92xe-visible']")
        hr.location_once_scrolled_into_view
        time.sleep(2)
        hours.append([i.get_attribute('aria-label') for i in driver.find_elements_by_xpath("//*[contains(@aria-label, 'busy at')]")])
    except NoSuchElementException:
        hours.append(np.nan)

    try:
        coordinates = driver.find_element_by_css_selector('meta[itemprop=image]').get_attribute('content')
        coordinates = coordinates.split('?center=')[1].split('&zoom=')[0].split('%2C')
        lat.append(coordinates[0])
        long.append(coordinates[1])
    except NoSuchElementException:
        lat.append(np.nan)
        long.append(np.nan)

    print(len(ParksNames))
    print(len(rating))
    print(len(total_ratings))

# Closing the Chrome window
driver.close()

#storing the data as a pandas dataframe
PG= pd.DataFrame(data={'ParksNames':ParksNames, 'business_category':business_cat, 'rating':rating, 'total_ratings':total_ratings, 'latitude':lat, 'longitude':long ,
'Hours': hours})
PG.to_csv('parks_trial4.csv', index=False)
```

Code for Phase 3- Automating extraction of the reviews of parks along with their nos. of rating, their rating value and their location coordinates as referrence:

```
from selenium import webdriver
from selenium.webdriver.common.by import By
from selenium.webdriver.support.ui import WebDriverWait
from selenium.webdriver.support import expected_conditions as EC
from selenium.webdriver.common.keys import Keys
from selenium.common.exceptions import NoSuchElementException, TimeoutException, ElementNotInteractableException, ElementClickInterceptedException
```

```
from tqdm import tqdm_notebook as tqdmn
import pandas as pd
import numpy as np
import folium
import time, re
driver= webdriver.Chrome(“C:\Program Files (x86)\Chromedriver.exe”)
driver.implicitly_wait(20)

import pandas as pd
with open(‘D:/Thesis/gis&sats file/UFD/Parks/sentiment_analysis/Parks(reviews).csv’) as file:
   Parks = file.read().splitlines()

# Here’s the big loop iterating over the competiton list :
for Park in tqdmn(Parks, leave=False, desc=’3. Extracting the data’) :
   ParksNames=[]
   rating = []
   total_ratings = []
   business_cat = []
   reviews_text=
   reviews_time=
   lat = []
   long = []

   # URL making :
   url = ‘https://www.google.com/maps/search/’ + Park + ‘’+ ‘’ + ‘ Metropolitan City of Milan, Italy’
   driver.get(url)

    # Waiting for the name of the business to load and be visible. If it fails, skip to next business in competition list :
   try :
      WebDriverWait(driver,25).until(EC.visibility_of_element_located((By.CLASS_NAME,”x3AX1-LfntMc-header-title-ij8cu”)))
   except (NoSuchElementException, TimeoutException) as e :
      continue

   # Extracting the data and putting it into the empty lists we defined earlier :
   try:
      ParksNames.append(driver.find_element_by_xpath(‘//h1[@class=”x3AX1-LfntMc-header-title-title gm2-headline-5”]’).text)
```

```
    except NoSuchElementException :
        ParksNames.append(np.nan)
     try:
        rating.append(driver.find_element_by_xpath(('//span[@class="aMPvhf-fI6EEc-KVuj8d"]')).text)
    except NoSuchElementException :
        rating.append(np.nan)
    try:
business_cat.append(driver.find_element_by_xpath('//button[@jsaction="pane.rating.category"]').text)
    except NoSuchElementException:
        business_cat.append(np.nan)
    try:
        tr= driver.find_element_by_xpath("//div[@class='jANrlb']")
        tr.location_once_scrolled_into_view
        time.sleep(2)
        total_ratings.append(driver.find_element_by_xpath("//button[@class='HHrUdb gm2-button-alt HHrUdb-3pZbf']").text)
    except NoSuchElementException:
        total_ratings.append(np.nan)

    #more reviews button :
    button= driver.find_element_by_xpath('//button[@class="HHrUdb gm2-button-alt HHrUdb-v3pZbf"]').click()
    time.sleep(2)

     ele= driver.find_element_by_xpath('//*[@class="siAUzd-neVct section-scrollbox cYB2Ge-oHo7ed cYB2Ge-ti6hGc"]')
    ele.send_keys(Keys.END)
    try :
        time.sleep(10)
        ele.send_keys(Keys.END)
    except NoSuchElementException:
          np.nan
    time.sleep(10)

    try :
        time.sleep(10)
        ele.send_keys(Keys.END)
    except NoSuchElementException:
          np.nan
```

```
time.sleep(10)

try :
   time.sleep(10)
   ele.send_keys(Keys.END)
except NoSuchElementException:
     np.nan
time.sleep(10)

try :
   time.sleep(10)
   ele.send_keys(Keys.END)
except NoSuchElementException:
     np.nan
time.sleep(10)

try :
   time.sleep(10)
   ele.send_keys(Keys.END)
except NoSuchElementException:
     np.nan
time.sleep(10)

try :
   time.sleep(10)
   ele.send_keys(Keys.END)
except NoSuchElementException:
     np.nan
time.sleep(10)

try :
   time.sleep(10)
   ele.send_keys(Keys.END)
except NoSuchElementException:
     np.nan
time.sleep(10)
```

```
try :
   time.sleep(10)
   ele.send_keys(Keys.END)
except NoSuchElementException:
     np.nan
time.sleep(10)

try :
   time.sleep(10)
   ele.send_keys(Keys.END)
except NoSuchElementException:
     np.nan
time.sleep(10)

try :
   time.sleep(10)
   ele.send_keys(Keys.END)
except NoSuchElementException:
     np.nan
time.sleep(10)

try:

   reviews_text.append([i.text for i in driver.find_elements_by_xpath("//*[@class='ODSEW-ShBeI-text']")])
   reviews_time.append([i.text for i in driver.find_elements_by_xpath("//*[@class='ODSEW-ShBeI-RgZmSc-date']")])
   time.sleep(10)
   print(reviews_text)
except NoSuchElementException:
   hours.append(np.nan)

try:
   coordinates = driver.find_element_by_css_selector('meta[itemprop=image]').get_attribute('content')
   coordinates = coordinates.split('?center=')[1].split('&zoom=')[0].split('%2C')
   lat.append(coordinates[0])
   long.append(coordinates[1])
except NoSuchElementException:
   lat.append(np.nan)
```

```
        long.append(np.nan)

    #storing the data as a pandas dataframe
    PG = pd.DataFrame(data={'ParksNames':ParksNames, 'rating':rating, 'total_ratings':total_ratings, 'reviews_text':(i for i in reviews_text),'reviews_time':reviews_
time, 'latitude':lat, 'longitude':long})
    PG.to_csv('Park.csv', index=False)
    print(len(ParksNames))
    print(len(rating))
    print(len(total_ratings))
    print(len(reviews_text))
    print(len(reviews_time))

# Closing the Chrome window
driver.close()
```

Code for Phase 4- Automating extraction of the reviews of parks along with their nos. of rating, their rating value and their location coordinates as referrence:

```
import pandas as pd
import nltk
from nltk.tokenize import word_tokenize
from nltk.stem import PorterStemmer
from nltk.stem import WordNetLemmatizer
import re
import string
import textblob
from textblob import TextBlob
from nltk.corpus import stopwords
nltk.download('stopwords')
p =pd.read_csv('D:/Thesis-/gis&sats file/UFD/Parks/sentiment_analysis/parks_nlp_processing.csv')
p.reviews_text

#Remove punctuations:
p["clean_text"]= p["reviews_text"].apply(lambda x : "".join(re.sub("[.,!()'...']","",str(x))))
#Remove Numbers:
p["clean_text"].replace("\d+","", regex=True,inplace=True)
#Remove anything that is not a word or space(to remove any emojis:
```

```
p["clean_text"]= p["clean_text"].apply(lambda x : "".join(re.sub("[^\w+\s]",'',(x))))

#wordcount:
def word_count(text):
        wcount= (len(text.split()))
        return wcount
p["wordcount"]= p["clean_text"].apply(lambda x: word_count(x))

#Remove stopwords:
#defining the stopword object:
stop= set(stopwords.words('english'))

def rem_en(input_text):
   words=input_text.lower().split()
   noise_free_words=(word for word in words if word not in stop)
   noise_free_text= " ".join(noise_free_words)
   return noise_free_text
p["clean_text"]= p["clean_text"].apply(lambda x :  rem_en(x))

#Tokenize text:
from nltk.tokenize import RegexpTokenizer
tokeniser = RegexpTokenizer(r'\w+')
p["clean_text"] = p["clean_text"].apply(lambda x: tokeniser.tokenize(x))

# Normalize the texts (Stemming):
from nltk.stem.porter import PorterStemmer
#defining the object for stemming
stemmer = PorterStemmer()
#defining a function for stemming
def stemming(text):
   stem_text = [stemmer.stem(word) for word in text]
   return stem_text
p["txt__stemmed"]=p["clean_text"].apply((lambda x: stemming(x)))

# Normalize the texts (Lemmatizing):
nltk.download('wordnet')
```

```
from nltk.stem import WordNetLemmatizer
lemmatizer = WordNetLemmatizer()
p["txt_lemmat"] = p["clean_text"].apply(lambda texts: [lemmatizer.lemmatize(text, pos='v') for text in texts])

#no. of token:
def token_count(text):
        wcount= (len(text))
        return wcount
p["tokencount"]= p["clean_text"].apply(lambda x: token_count(x))

#Sentiment analysis using textblob: (Polarity)
def sentiments_ana(x):
   if x is not None:
               return TextBlob(x).sentiment.polarity
p["sentiment_score"]=p["txt_lemmat"].apply( lambda texts: [sentiments_ana(text) for text in texts])

#totalizing sentiments of sentences:
def totalizing( texts_list):
   total =0
   for ele in range(0, len(texts_list)):
      total = (total +texts_list[ele])
   return total
p["sentiment_score_total"]= p["sentiment_score"].apply(totalizing)

#Average polarity of each sentence:
p["Avg_pol"]=p["sentiment_score_total"]/p["tokencount"]

#Sentiment analysis using textblob: (Subjectivity)
def sentiments_sub(x):
   if x is not None:
               return TextBlob(x).sentiment.subjectivity
p["sentiment_sub"]=p["txt_lemmat"].apply( lambda texts: [sentiments_sub(text) for text in texts])

#totalizing sentiments of sentences:
def total( texts_list):
   total =0
```

```
    for ele in range(0, len(texts_list)):
        total = total +texts_list[ele]
    return total
p["sentiment_sub_total"]= p["sentiment_sub"].apply(total)

#Average subjectivity of each sentence:
p["Avg_sub"]=p["sentiment_sub_total"]/p["tokencount"]

p[["ParksNames","reviews_text","clean_text","wordcount","txt__stemmed","txt_lemmat","sentiment_score","sentiment_score_total","Avg_pol","tokencount","sentiment_sub","sentiment_sub_total","Avg_sub"]]

#To save the columns as a new csv:
p.to_csv('sentiment_analysis.csv')
```

Code for Phase 5 : Topic Modelling to interpret contexts of the reviews
Repeate the NLP process but saving the data as variable rather than a column of pandas data frame the final step of lemmatized reviews continue with the following code :

```
#Topic Modelling with Genssim:
dictionary = corpora.Dictionary(txt_lemmat)
doc_term_matrix= [dictionary.doc2bow(i) for i in txt_lemmat]

#object for lda modelling using gensim:
LDA= gensim.models.ldamodel.LdaModel

#Building the LDA model:
lda_model=LDA(corpus=doc_term_matrix,id2word=dictionary, num_topics=4, random_state=100,chunksize=1000, update_every= 1, passes=500 )
lda_model.save('lda-topics')

# Visualize the topics
pyLDAvis.enable_notebook()
vis = pyLDAvis.gensim_models.prepare(lda_model, doc_term_matrix, dictionary)
vis
lda_model.print_topics()
```

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