URBREATH [101139711]

Systemic Integration of Transformative Technical and Nature-based Solutions to Improve Climate Neutrality of European Cities and Regions and tackle Climate Change: the URBreath Approach

D3.7: AI Models for Socioeconomic, Community, Organisational and Citizen Well-being– Version 1

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Disclaimer

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Executive Summary

This deliverable focuses on the development of predictive models aimed at evaluating the impacts of Nature-Based Solutions (NBS) on socioeconomic and environmental metrics in urban areas. It details the methodologies, data requirements, and preliminary results achieved during this phase of the URBREATH project, establishing a foundation for future refinements and integration into the project's broader framework. The models address key urban metrics, including economic activity, crime rates, property values, pedestrian density, public transport access, and overall citizen well-being. By leveraging remote sensing data, open-access repositories, and contributions from end-user partners, the deliverable emphasizes a data-driven approach to understanding the effects of NBS on urban systems.

Significant progress has been made in identifying critical input parameters and acquiring data from diverse sources, including NDVI, nighttime light intensity, and socioeconomic indicators. Preliminary predictive models have been designed using machine learning techniques, enabling the analysis of how NBS interventions affect urban dynamics. Input/output analyses for each model are presented, illustrating how data inputs inform predictions about the impacts of NBS. However, challenges remain in collecting high-resolution localized data and aligning datasets across spatial and temporal scales, which necessitate ongoing collaboration with end-user partners and iterative model improvements.

Future efforts will focus on refining these predictive models, integrating them into the URBREATH platform, and deploying visualizations to enhance accessibility and usability. These developments will support urban planners and policymakers in evaluating and implementing NBS interventions. By providing actionable insights, the project aims to contribute to sustainable, equitable, and resilient urban development.

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List of Terms and Abbreviations

Abbreviation	Definition
NBS	Nature-Based Solutions
NDVI	Normalized Difference Vegetation Index
PM2.5	Particulate Matter ≤2.5 micrometers
PM10	Particulate Matter ≤10 micrometers
GDP	Gross Domestic Product
GIS	Geographic Information System
GTFS	General Transit Feed Specification
VIIRS	Visible Infrared Imaging Radiometer Suite
MODIS	Moderate Resolution Imaging Spectroradiometer
ESA	European Space Agency
OSM	OpenStreetMap
OECD	Organisation for Economic Co-operation and Development
AI	Artificial Intelligence
IoT	Internet of Things
KPI	Key Performance Indicator
WP	Work Package
UHI	Urban Heat Island
NBS	Nature-Based Solutions

1 Introduction

The URBREATH project aims to develop advanced data-driven tools and models to evaluate the socioeconomic, organizational, and citizen well-being impacts of Nature-Based Solutions (NBS) in urban environments. NBS are interventions that leverage natural systems to address urban challenges such as air pollution, climate change, and socioeconomic inequalities. These solutions are increasingly recognized for their potential to create sustainable and resilient urban ecosystems.

This deliverable focuses on the development of predictive models that assess the effects of NBS on various urban metrics, including economic activity, crime rates, property values, and mobility. By combining remote sensing data, socioeconomic indicators, and urban metrics, these models provide a comprehensive framework for understanding how NBS can influence urban well-being.

The document outlines the scope, methodologies, and data requirements for these models. It describes the integration of open-access data repositories with contributions from end-user partners to ensure localized relevance and scalability. Additionally, the deliverable presents an input/output analysis for each model, highlighting the relationships between input parameters and the predicted outcomes.

The initial phase of the project emphasizes building the foundational components necessary for model development, including data acquisition, preprocessing, and preliminary analyses. Future phases will focus on refining the models, integrating them into the URBREATH platform, and deploying visualization tools to support stakeholder decision-making.

This deliverable provides an overview of the current progress and outlines the next steps in model development, integration, and deployment. By enabling the systematic evaluation of NBS, the project aims to support urban planners and policymakers in making informed decisions that promote sustainable, equitable, and resilient urban environments.

1.1 Purpose and Scope

The purpose of this deliverable is to document the development of predictive models that assess the socioeconomic and environmental impacts of Nature-Based Solutions (NBS) on urban well-being. These models aim to provide insights into how NBS can influence key urban metrics, such as economic activity, crime rates, property values, mobility, air quality, and overall citizen well-being. The deliverable focuses on the data requirements, methodologies, and preliminary results of these models, offering a foundation for their future refinement and integration into the URBREATH platform.

The scope of this report encompasses the following aspects:

- Model Development: Designing and implementing predictive models that leverage remote sensing data, socioeconomic indicators, and urban metrics to evaluate the effects of NBS.

- Data Acquisition and Preprocessing: Identifying, collecting, and preparing relevant data from open repositories and end-user partners, ensuring adequate spatial and temporal coverage.
- Preliminary Analysis: Conducting input/output analyses to establish relationships between data parameters and the predicted impacts of NBS interventions.

1.2 Approach for Work Package and Relation to other Work Packages and Deliverables

This deliverable establishes the foundation for predictive models evaluating the socioeconomic impacts and impacts towards citizen's well-being of Nature-Based Solutions (NBS), directly informing multiple project actions and future iterations of this deliverable. It supports WP4 by providing key inputs for decision-making tools, such as digital twins and KPI dashboards, enabling dynamic evaluation of NBS impacts.

In WP6, the models play a critical role in monitoring and validating the long-term effects of NBS implementations. Furthermore, the transferable frameworks developed here support WP7 by facilitating the scaling and replication of NBS strategies across different urban contexts. This deliverable is also interconnected with WP2 by utilizing harmonized datasets and informing data requirements.

As an iterative process, this deliverable lays the groundwork for future versions, incorporating feedback, refined data, and improved model accuracy to further align with the project's objectives.

1.3 Methodology and Structure of the Deliverable

This deliverable follows a structured approach to developing predictive models for assessing the impacts of Nature-Based Solutions (NBS) on urban well-being. The deliverable is organized into sections that reflect the sequential stages of this process.

The structure of the deliverable is as follows:

- Section 2: Tool and Model Descriptions – This section provides an overview of the predictive models, detailing their purpose, input parameters, and expected outputs. It also discusses the underlying methodologies used in their development.
- Section 3: Data Needs and Analysis – This section outlines the data requirements for each model, assessing the availability and quality of data sources. It includes a preliminary input/output analysis to illustrate the connections between data inputs and the models' predictive capabilities.
- Section 4: Conclusions and Future Work – This section summarizes the progress made, highlights challenges encountered, and presents the next steps, including model refinement, integration into the URBREATH platform, and deployment for real-world applications.

2 Tool and model Descriptions

This section outlines the current progress in model development, focusing on data acquisition, preliminary analyses, and technological setup. It also highlights the challenges encountered and the steps planned for the next phases, emphasizing data refinement, model optimization, and deployment strategies.

Understanding and enhancing citizen well-being requires a data-driven approach to modeling the various socioeconomic parameters that shape urban life. In the context of the URBREATH project, these parameters—economic activity, crime statistics, property prices and rent trends, pedestrian density, and public transport accessibility—are pivotal for assessing the impact of Nature-Based Solutions (NBS) on urban environments. Each parameter provides unique insights into the dynamics of urban development, community health, and the quality of life for residents.

The development of these models is driven by the overarching goal of enabling urban planners and policymakers to make informed decisions that promote sustainable, equitable, and vibrant cities. These models rely on advanced machine learning techniques, with regression frameworks tailored to predict specific outcomes for each parameter. The use of state of the art neural network architectures, such as bidirectional Long Short-Term Memory (LSTM) networks and Transformer architectures, ensures that the models are capable of handling complex, multivariate datasets while capturing temporal and spatial dependencies. While these architectures are currently selected for their state-of-the-art performance, future developments may lead to adjustments or refinements to further enhance their predictive capabilities.

Central to the modeling approach is the integration of remote sensing data, demographic statistics, and socioeconomic indicators. Remote sensing, particularly through nighttime light intensity, air quality indices, and vegetation metrics, provides high-resolution, spatially distributed data that serves as a powerful proxy for many urban phenomena. Complementing these datasets with census information and socioeconomic metrics like GDP, income levels, and housing data ensures a comprehensive understanding of the underlying factors driving urban changes.

Horizontally, the overarching goal of these models is to provide a unified framework that enables stakeholders to design and assess the socioeconomic impacts of Nature-Based Solutions (NBS). This framework allows users to "draw" a proposed NBS on a map, which dynamically updates remote sensing values such as Normalized Difference Vegetation Index (NDVI) and Land Use/Land Cover (LULC) in a predefined manner. The updated inputs are then fed into the models to run inference, providing projected socioeconomic outcomes such as changes in economic activity, crime rates, property values, or mobility patterns. To achieve robust and generalized predictions, the models will be trained on data not only from the district under study but also from similar areas, including open datasets from other cities and countries outside the consortium. This approach ensures that the models are versatile and capable of delivering insights even in contexts with varying data availability or urban conditions.

The following sections delve into the individual models, providing descriptions of the socioeconomic parameters, their relevance to citizen well-being, the data and methods used for modeling, and the applications of the resulting predictions. These models aim to bridge the gap between urban planning and citizen-centric solutions, driving sustainable development and improved quality of life across diverse urban contexts.

2.1 Detailed model descriptions

2.1.1 Economic Activity Model

Economic activity, defined as the production, distribution, and consumption of goods and services within a specific area, serves as a cornerstone of urban development and a fundamental determinant of citizen well-being. Higher levels of economic activity often correlate with increased incomes, which enhance the quality of life by improving access to goods and services. Economic prosperity attracts businesses, fostering diverse economic opportunities and encouraging infrastructure investments in transportation systems, communication networks, and public amenities, further enriching urban living conditions.

Studies highlight the critical role of economic activity as a driver of urban development. For example, cities with high economic activity tend to provide better public services and infrastructure, significantly contributing to residents' well-being. Examples such as Singapore and Dubai illustrate how robust economic environments can transform urban areas into global hubs for business and innovation (Henderson et al., 2012; Shi et al., 2014). Moreover, satellite imagery data reveals a positive correlation between nighttime light intensity and regional economic output, validating the use of nighttime light intensity as a proxy for economic activity (Henderson et al., 2012).

Economic activity data can be sourced from national statistical agencies, local economic surveys, and business registries. Remote sensing data, particularly nighttime light intensity captured by the Visible Infrared Imaging Radiometer Suite (VIIRS), provides a spatially detailed proxy for economic patterns. Tools like Google Earth Engine enable large-scale analysis of such datasets, offering real-time insights.

In this model, nighttime light intensity serves as the primary data source, supplemented by census and GDP data to improve accuracy and contextual relevance. Nighttime light intensity data is derived from satellite imagery captured by systems like VIIRS, which monitor artificial illumination during nighttime to track urban lighting, industrial operations, and infrastructure use. This data is highly correlated with GDP, population density, and development levels, making it an effective indicator of economic activity. For instance, regions with high light intensity typically represent active commercial hubs or densely populated urban areas, while areas with low light intensity often correspond to rural or underdeveloped regions.

The methodology begins with acquiring nighttime light data from platforms such as NASA's EarthData and NOAA's Earth Observation Group (NOAA, n.d.). This data is globally available and provides a uniform measure of light intensity across diverse geographic and socioeconomic contexts. Preprocessing involves aligning the data with district boundaries using Geographic Information System (GIS) tools, normalizing it to account for seasonal variations, and filtering anomalies caused by temporary events.

While nighttime light intensity offers valuable insights, it has limitations. For example, it cannot distinguish between residential lighting, industrial operations, or public infrastructure. To address this, the model will incorporate census data and GDP information (e.g. average citizen income, business bureau information) to contextualize light intensity measurements. Census data adds demographic insights, such as population density, labor force participation, and urbanization levels, while GDP data anchors the model in economic terms.

During the model training phase, historical nighttime light intensity data serves as the primary input, while GDP and census-derived features act as complementary predictors. Regression-based machine learning algorithms are used to establish the relationship between these inputs and known economic indicators. The resulting model aims to predict district-level economic activity, enabling the simulation of future scenarios where Nature-Based Solutions (NBS) influence urban landscapes.

2.1.1.1 Connection with Case Studies

The Economic Activity Model utilizes nighttime light intensity as a proxy for measuring economic activity, aligning well with urban regeneration efforts in case study cities such as Cluj-Napoca and Tallinn. For instance, in Cluj-Napoca's Iris Neighborhood, tracking nighttime light intensity before and after NBS implementation could provide insights into economic revitalization in redesigned urban areas. Similarly, Tallinn's Linnahall Area, currently underutilized and disconnected from the city center, could benefit from such metrics to evaluate the economic impact of making the area more accessible and attractive. Insights from D2.4, particularly baseline data on socioeconomic conditions, offer a crucial reference for calibrating this model to reflect localized economic dynamics and ensure its relevance to urban regeneration projects.

2.1.2 Crime Statistics Model

Crime statistics are vital indicators of safety, directly influencing the quality of life and well-being of citizens. A safe environment fosters a sense of security, enabling individuals to live, work, and socialize without fear. High crime rates disrupt daily life, exacerbate mental health issues, hinder economic opportunities, and weaken social cohesion. The model developed for URBREATH leverages geospatial crime mapping, complemented by demographic and socioeconomic data, to predict crime rates and understand their implications for citizen well-being.

Safety is a fundamental human need, and its absence can severely impact psychological and emotional health. Fear of crime can lead to reduced mobility, as individuals avoid certain areas or times of the

day, restricting access to social and economic opportunities. This diminished freedom particularly affects marginalized communities, perpetuating cycles of inequality. Research has shown that neighborhoods with high crime rates often experience economic stagnation, as businesses hesitate to invest and residents with means relocate to safer areas (Sampson, 2012). This dynamic creates cycles of deprivation, where unsafe conditions disproportionately impact the most vulnerable.
The model quantifies crime's impact on citizen well-being by analyzing its spatial and demographic context. Geospatial crime mapping forms the foundation of this approach, using data sourced from open repositories and local law enforcement agencies (Johnson & Bowers, 2020). Crime incidents are geotagged and aggregated to district boundaries, enabling the identification of high-risk zones or "hotspots." These hotspots often correlate with urban vulnerabilities, such as poorly lit streets, abandoned buildings, or insufficient public spaces. Addressing these infrastructural deficits is key to promoting safety and enhancing quality of life.

Demographic data from census sources adds depth to the model, offering insights into how different populations experience crime. For example, data on population density, age distribution, and socioeconomic conditions such as income and employment rates help identify at-risk groups. By integrating these factors, the model provides a nuanced understanding of crime's impact on diverse communities (United Nations Office on Drugs and Crime, 2021).

Socioeconomic conditions play a significant role in shaping crime patterns and their implications for well-being. Studies consistently show strong correlations between poverty, unemployment, and higher crime rates (Smith et al., 2017). For instance, economically disadvantaged neighborhoods often experience elevated rates of property crimes, vandalism, and theft. Such environments struggle to attract businesses, resulting in reduced services and employment opportunities, which further erode community stability.

Urban environmental factors are also critical in understanding crime dynamics. For instance, poorly lit streets or neglected public parks often become hubs for criminal activity, deterring their use and reducing their value as community assets (Johnson & Bowers, 2020). Conversely, well-maintained public spaces with adequate lighting and visibility have been shown to reduce crime and promote positive social interactions. By integrating environmental features such as lighting infrastructure, proximity to public parks, and transportation hubs, the model identifies infrastructural priorities for improving safety and citizen well-being.

The temporal dimension of crime is another key factor in understanding its effects on well-being. Seasonal changes, such as increased crimes during holidays, and long-term trends, like the rise of cybercrimes, require tailored strategies to address citizens' evolving needs. Analyzing these patterns helps anticipate challenges, ensuring that public safety measures remain proactive rather than reactive (Henderson et al., 2012).

The crime statistics model will operate as a predictive framework, enabling urban planners and policymakers to forecast the impact of crime on citizen well-being and design targeted interventions.

Historical crime data serves as the primary input, complemented by demographic and urban environmental factors.

2.1.2.1 Connection with Case Studies

This model plays a vital role in assessing the socioeconomic impact of NBS, particularly in cities like Leuven and Athens. For Leuven's Krakau Square, the model can monitor property price trends to evaluate both the benefits and potential risks, such as gentrification, associated with urban regeneration. In Athens, where pilot sites like Kypseli and Neos Kosmos focus on improving community spaces, tracking shifts in rental trends can offer insights into the socioeconomic ripple effects of such interventions. The property and housing baseline data included in D2.4 is essential for contextualizing these trends, ensuring the model captures the nuances of local housing markets.

2.1.3 Property Prices and Rent Trends

Property prices and rent trends serve as critical indicators of urban economic health, housing accessibility, and societal stability. These parameters reflect the cost of purchasing or renting residential and commercial properties, which directly impact citizens' quality of life. High property prices can signify economic growth and urban desirability but also risk creating affordability challenges, particularly for low- and middle-income households. By modeling property prices and rent trends, this study aims to understand their dynamics and implications for citizen well-being, enabling data-driven urban planning and policy-making.

Housing is a fundamental human need, and its affordability profoundly influences the well-being of individuals and communities. Affordable housing ensures that families can allocate resources to other essential areas such as healthcare, education, and nutrition. Conversely, unaffordable housing can strain household budgets, leading to financial stress and reduced access to services. High housing costs can also contribute to displacement, forcing long-time residents to relocate to less desirable areas, disrupting social ties, and deepening inequalities.

From a societal perspective, stable property markets promote social cohesion by reducing the risk of displacement and fostering long-term community development. Areas with balanced property prices are more likely to retain diverse populations, contributing to vibrant and inclusive neighborhoods. However, rising property prices, often driven by speculative investments or urban gentrification, can marginalize vulnerable populations. For instance, in cities like San Francisco and London, escalating housing costs have created affordability crises, disproportionately impacting low-income and minority residents (Zillow, 2022; Eurostat, 2021).

Rent trends are equally significant, as they influence housing accessibility for transient populations, such as students, workers, and migrants. In many urban areas, rising rents can outpace wage growth, leaving renters with limited disposable income and constraining their ability to save or invest. This dynamic can perpetuate cycles of poverty and reduce social mobility. Addressing these challenges requires a nuanced understanding of the factors driving property prices and rent trends and their implications for urban life.

Empirical studies underscore the strong relationship between housing affordability and quality of life. For instance, research in European cities has shown that affordable housing reduces financial stress and enhances social stability (Eurostat, 2021). Conversely, studies in the United States have highlighted how rising rents contribute to economic disparities and reduce social mobility (Zillow, 2022). These findings underscore the need for proactive housing policies informed by data-driven models.

The model developed for URBREATH uses property prices and rent trends as dependent variables, influenced by a combination of demographic, socioeconomic, and urban environmental factors. Data on property transactions and rental agreements are sourced from real estate platforms like Zillow, government property registries, and housing market surveys. These datasets provide detailed information on property values, transaction volumes, and rental rates, enabling district-level analysis.
To contextualize property prices and rent trends, the model integrates demographic data such as population density, income levels, and education attainment. For instance, areas with higher average incomes often exhibit higher property prices, reflecting greater purchasing power and demand for premium housing. Similarly, densely populated districts may experience elevated rents due to limited housing supply relative to demand.

Urban environmental factors also play a critical role. Proximity to amenities such as parks, schools, transportation hubs, and commercial centers can significantly influence property values. Properties located near well-maintained green spaces or within walking distance of public transit stations tend to command higher prices and rents due to their enhanced livability. Conversely, properties near sources of pollution or noise, such as industrial zones or busy highways, may see depressed values.

From a citizen well-being perspective, unaffordable housing creates multiple stressors. Households forced to allocate a significant portion of their income to housing often experience financial insecurity, limiting their ability to invest in education, health, and recreation. Furthermore, displacement due to rising rents disrupts social networks, eroding community ties and contributing to mental health challenges. On a broader scale, housing affordability crises can lead to increased homelessness, straining public resources and exacerbating urban inequalities.

Conversely, affordable and stable housing markets contribute to societal well-being by providing secure living conditions and promoting economic opportunities. When residents can afford housing within their means, they are better positioned to participate in community life, pursue education and career goals, and maintain their health and well-being. For example, Vienna’s public housing policies, which prioritize affordability and social inclusivity, have been lauded as a model for promoting urban equity and quality of life (OECD, 2021).

2.1.3.1 Connection with Case Studies

This model plays a vital role in assessing the socioeconomic impact of NBS, particularly in cities like Leuven and Athens. For Leuven's Krakau Square, the model can monitor property price trends to evaluate both the benefits and potential risks, such as gentrification, associated with urban regeneration. In Athens, where pilot sites like Kypseli and Neos Kosmos focus on improving community spaces, tracking shifts in rental trends can offer insights into the socioeconomic ripple effects of such interventions. The property and housing baseline data included in D2.4 is essential for contextualizing these trends, ensuring the model captures the nuances of local housing markets.

2.1.4 Urban Mobility Model

Mobility is a cornerstone of urban life, shaping how citizens navigate their environment and access essential services. Among the critical mobility parameters influencing citizen well-being are pedestrian density and public transport accessibility. These factors collectively determine the ease, safety, and sustainability of movement within urban areas, directly impacting health, economic activity, and social inclusion. By modeling these parameters, we aim to understand their dynamics and explore their role in enhancing urban environments through targeted interventions like Nature-Based Solutions (NBS).

Pedestrian density measures the number of people walking in a specific area at a given time. It serves as a proxy for the vibrancy and walkability of urban spaces, reflecting how conducive these areas are to active and sustainable modes of transport. High pedestrian density typically indicates active public spaces, well-connected sidewalks, and pedestrian-friendly infrastructure, contributing to a sense of safety and community cohesion. Conversely, areas with low pedestrian density often reflect automobile dependency, poorly maintained pedestrian infrastructure, or social barriers that discourage walking.
Walkability is closely tied to physical and mental health. Encouraging walking reduces reliance on vehicles, promoting physical activity and lowering risks of obesity, cardiovascular diseases, and related health conditions. It also minimizes air and noise pollution, improving environmental quality and fostering psychological well-being. Studies have shown that well-connected, walkable neighborhoods foster social interactions, strengthen community bonds, and enhance overall happiness (Speck, 2018).
Urban areas designed to prioritize pedestrians also see economic benefits. Local businesses thrive in high-foot-traffic areas, as pedestrians are more likely to engage in spontaneous purchases compared to vehicle users. Furthermore, walkable districts often attract tourism and investment, reinforcing economic activity. However, ensuring equitable access to walkable spaces is essential, as some neighborhoods face infrastructural challenges that deter walking, such as unsafe crossings, insufficient lighting, or poorly maintained sidewalks.

Public transport accessibility evaluates how easily residents can access transit services, considering proximity to transit stops, frequency of service, and network connectivity. Public transportation is a critical component of sustainable urban mobility, enabling citizens to reach employment centers, schools, healthcare facilities, and recreational areas. Well-connected transit networks reduce travel time, improve reliability, and promote equity by providing affordable mobility options, particularly for low-income residents.

Accessible public transport has significant implications for economic opportunities. Studies reveal that individuals with access to efficient public transit are more likely to find employment, as they can commute farther for work without significant cost increases (UITP, 2021). Public transit also reduces dependency on private vehicles, lowering traffic congestion, fuel consumption, and greenhouse gas emissions, contributing to a more sustainable urban environment.

To capture the dynamics of pedestrian density and public transport accessibility, the Urban Mobility model integrates geospatial, demographic, and urban infrastructure data. Pedestrian density will be measured using IoT sensors, mobile phone data, and manual foot traffic counts, which are spatially aligned with district boundaries. Public transport accessibility is evaluated through GIS-based analysis of transit networks, including the location of stops, service frequency, and connectivity between districts.

The model incorporates demographic data, such as population density, income levels, and car ownership rates, to contextualize mobility patterns. Urban features like proximity to green spaces, commercial hubs, and educational institutions are also included to assess how infrastructure supports or hinders mobility. For instance, areas with higher pedestrian density and public transport access near green spaces may reflect the benefits of well-planned NBS, such as increased recreational use and reduced car dependency.

From a citizen well-being perspective, pedestrian-friendly environments and accessible public transport enhance mobility, reduce transportation costs, and improve quality of life. Walkable neighborhoods encourage active lifestyles, fostering physical health and reducing healthcare costs. Public transportation promotes social inclusion by ensuring that all citizens, regardless of economic status, can access opportunities and services. The environmental benefits of reduced vehicle use, such as lower air pollution and greenhouse gas emissions, further enhance urban livability.

Conversely, the absence of pedestrian-friendly infrastructure or reliable public transport restricts mobility, increases transportation costs, and perpetuates social inequalities. Low-income communities disproportionately bear the burden of inadequate transit systems, limiting their access to employment and essential services. Addressing these gaps through targeted interventions can significantly improve equity and well-being. Empirical research highlights the benefits of integrating pedestrian density and public transport accessibility into urban planning. For instance, a study by UITP (2021) demonstrated that improved transit connectivity in urban areas increased employment rates and reduced commuting times. Similarly, Gehl (2010) emphasized the role of walkable public spaces in fostering community interactions and enhancing quality of life. These findings underscore the critical role of mobility parameters in shaping citizen well-being and sustainable urban development.

2.1.4.1 Connection with case studies

The Urban Mobility Model focuses on analyzing traffic patterns and accessibility improvements, essential for cities like Aarhus and Kajaani. In Aarhus's Vesterbro Torv Square, where traffic modifications and greening efforts are underway, the model can assess reductions in motorized mobility and shifts toward pedestrian and bicycle use. For Kajaani's Maasto Area, the model can explore how enhanced water management structures and green corridors improve accessibility and connectivity for residents. The mobility baselines and urban planning insights detailed in D2.4 provide critical inputs for refining the model's predictions, ensuring it aligns with the cities' sustainability and mobility enhancement goals.

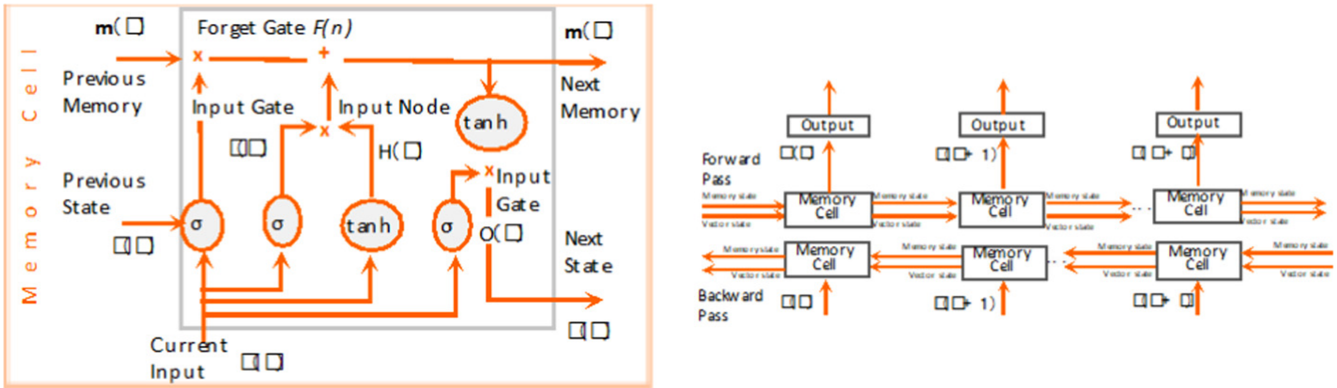
2.1.5 Technological Backbone of Socioeconomic Models

The socioeconomic models developed for the URBREATH project are underpinned by a robust technological backbone designed to ensure high predictive accuracy and adaptability. A pool of candidate models has been defined, and each socioeconomic parameter is modeled as a regression problem. This approach allows for precise predictions of numerical outcomes, such as GDP growth, crime rates, property prices, and pedestrian density, based on the input variables derived from remote sensing and socioeconomic data.

The technological framework leverages state-of-the-art machine learning techniques, focusing on advanced regressor architectures such as bidirectional Long Short-Term Memory (LSTM) networks and Transformer models. These architectures are well-suited for capturing complex temporal, spatial, and multivariate relationships inherent in the data. Additionally, the hyperparameters for each model will be tuned to maximize performance. To efficiently train and evaluate a large number of candidate architectures, the project uses the HYDRA tool, a sophisticated framework for hyperparameter optimization and model selection.

LSTM Based Approaches

Bidirectional Long Short-Term Memory (LSTM) networks are an extension of traditional recurrent neural networks (RNNs), designed to handle sequential data by capturing dependencies across time. Traditional LSTMs process data in a single direction, either forward or backward. However, bidirectional LSTMs enhance this capability by processing input sequences in both directions simultaneously, allowing the model to learn from both past and future contexts. This feature makes them particularly effective for time-series regression problems, where understanding trends and contextual relationships is critical. An illustration of the LSTM cell and how it is unfolded over multiple sample inputs is presented below.



(a) (b)

Figure 1: (a) The memory cell of an LSTM network and (b) a bidirectional LSTM unfolded through time (Bakalos et. Al. 2021)

The structure and building blocks of an LSTM network are:

1. Input Layer: Processes multivariate input data, such as normalized remote sensing variables (e.g., NDVI, nighttime light intensity) and socioeconomic indicators.
2. LSTM Units: Each unit contains a memory cell that retains long-term dependencies and three gates (input, forget, and output gates) that regulate the flow of information.
   a. The input gate determines which information from the input should be added to the memory cell.
   b. The forget gate decides what information to discard from the cell state.
   c. The output gate controls the final output of the cell.
3. Bidirectional Layer: Combines forward and backward passes, enabling the model to learn from both past and future time steps simultaneously.
4. Dense Layer: Maps the learned features to the target output, such as crime rates or property prices.
5. Output Layer: Produces the final regression output.

Bidirectional LSTMs excel at capturing temporal dynamics and are ideal for problems where contextual dependencies play a significant role. By modeling socioeconomic parameters with this architecture, the models can incorporate trends and patterns over time, leading to more accurate predictions.

Transformer Based Approaches

Transformer models, originally developed for natural language processing (NLP), have emerged as a powerful architecture for a wide range of tasks, including time-series forecasting and regression. Unlike RNNs, Transformers do not rely on sequential data processing, allowing them to handle long-range dependencies efficiently. The self-attention mechanism, a core component of the Transformer architecture, enables the model to weigh the importance of different input features dynamically.

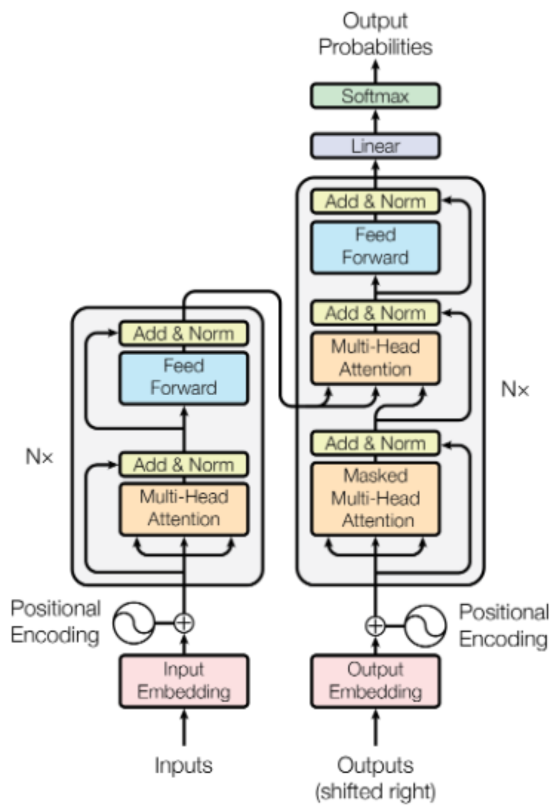


Figure 2: The Transformer Model Architecture (Vaswani, 2017)

The structure and building blocks of a Transformer network are :

1. Input Embedding Layer: Transforms input features into a fixed-dimensional representation suitable for the Transformer.
2. Positional Encoding: Adds positional information to the input embeddings, allowing the model to capture the order of input data.
3. Self-Attention Mechanism: Computes attention scores for each input feature relative to all others, enabling the model to focus on the most relevant features.
4. Feedforward Layers: Apply dense connections to refine the learned representations.
5. Encoder and Decoder Blocks: In regression tasks, only the encoder stack is typically used to process input features and generate predictions.
6. Output Layer: Produces the regression output, mapping learned representations to numerical predictions.

Transformers are particularly effective in handling complex, multivariate datasets with non-linear relationships. Their parallelized architecture ensures efficient training on large datasets, making them suitable for modeling high-dimensional socioeconomic parameters.

Parallel Training & Hyperparameter Tuning

Hyperparameter tuning is a critical and often resource-intensive phase in the development of high-performance machine learning models. It involves optimizing a set of parameters that control the learning process, such as learning rate, number of layers, dropout rates, and batch sizes. The effectiveness of any machine learning model depends not only on its architecture but also on the careful tuning of these hyperparameters. To automate and streamline this process, the URBREATH project employs the HYDRA tool, a state of the art framework for hyperparameter optimization and model selection.

HYDRA (Hydra AI, no date) is designed to address the challenges of training complex deep learning models like bidirectional LSTMs and Transformers, which require extensive experimentation to achieve optimal performance. By automating the exploration of hyperparameter configurations and deploying models across distributed computing resources, HYDRA significantly reduces the time and effort needed for model development. It is a scalable and flexible hyperparameter optimization platform that integrates multiple optimization algorithms with parallel training capabilities. It is particularly suited for large-scale experiments involving deep architectures. HYDRA's architecture supports a wide range of optimization strategies, including grid search, random search, Bayesian optimization, and evolutionary algorithms, making it adaptable to different modeling needs.

The tool operates in a modular fashion, allowing users to define their model architectures and hyperparameter search spaces. HYDRA then automatically generates candidate configurations, trains models, evaluates their performance, and selects the best-performing configuration based on predefined metrics.

The deployment of HYDRA in the URBREATH project follows a systematic workflow designed to optimize the performance of socioeconomic models:

1. **Defining the Search Space:** For each socioeconomic parameter, a set of hyperparameters and their respective ranges are defined. For example, in the crime statistics model, hyperparameters include the number of LSTM units, dropout rates, learning rate, and batch size. Similarly, for Transformer-based models, hyperparameters such as the number of attention heads, feedforward layer size, and positional encoding schemes are specified.
2. **Generating Candidate Configurations:** HYDRA automatically generates candidate configurations based on the chosen optimization strategy. For Bayesian optimization, it predicts the performance of configurations using a probabilistic model and focuses on exploring the most promising areas of the hyperparameter space.
3. **Parallel Training and Evaluation:** Each configuration is trained as a separate model on a distributed computing cluster. HYDRA ensures that multiple configurations are trained simultaneously, significantly reducing the time required to explore the search space. Each model is evaluated using a predefined metric, such as MAE or R^2, to assess its performance on validation data.
4. **Ranking and Selection:** Once training is complete, HYDRA ranks the models based on their evaluation scores. The best-performing configuration for each socioeconomic parameter is selected for final deployment.

5 **Iterative Refinement:** Based on the initial results, the hyperparameter ranges or optimization strategy may be refined. For example, if grid search reveals specific high-performing regions, Bayesian optimization can then focus on those areas for further exploration.

2.2 Current Development Status and next steps

The development of the socioeconomic models within the URBREATH project has progressed over the first 12 months, with efforts focused on laying a strong foundation for achieving the project's goals. This initial phase primarily revolved around problem definition, data source identification, stakeholder engagement, and establishing the technological backbone required for model development and deployment.

During this period, a thorough problem definition was conducted to refine the scope of each socioeconomic parameter model, ensuring alignment with project objectives and stakeholder expectations. This process involved extensive dialogues with end-user cities to understand their specific interests, challenges, and priorities. These discussions were instrumental in tailoring the models to address the unique requirements of different urban contexts, ensuring practical applicability and relevance.

Parallel to this, substantial progress was made in identifying and acquiring data sources. Efforts were directed towards remote sensing data, socioeconomic datasets, and demographic statistics, forming the core inputs for the models. A major milestone achieved during this phase was the successful collection of remote sensing data for Madrid, covering the past 10 years. This dataset includes key metrics such as NDVI, land use and land cover (LULC), air quality indices (e.g., PM10, PM2.5), and nighttime light intensity, providing a comprehensive temporal and spatial foundation for analysis. The data pipeline established for Madrid is fully operational and will be replicated for other cities participating in the project, ensuring consistency and scalability.

While remote sensing data collection for Madrid is complete, the process of gathering additional data sources remains ongoing. This includes socioeconomic indicators like GDP, income levels, crime statistics, property prices, and mobility data, which are being sourced from government agencies, public platforms, and stakeholder collaborations. These efforts are further detailed in the next section, where specific challenges and solutions related to data collection are described.

Looking ahead to the next development period, the project will focus on several critical areas to advance the models:

1 Increasing Granularity of Remote Sensing Data: Where necessary, efforts will be made to enhance the spatial and temporal resolution of the remote sensing datasets. This may involve integrating data from higher-resolution sensors or employing data fusion techniques to refine existing datasets.

2 Spatial and Temporal Data Alignment: A key step in preparing the models is aligning data from diverse sources to ensure consistency across spatial boundaries and timeframes. This will involve GIS tools and preprocessing techniques to harmonize datasets, enabling seamless integration into the models.

3 Initial Model Training: With the data pipeline for Madrid complete and ongoing data acquisition for other cities, initial model training is set to commence. This phase will involve validating the technological backbone by deploying the bidirectional LSTM and Transformer architectures to generate preliminary results. These results will inform iterative refinements to improve model performance and reliability.

3 Data Needs and Data Analysis

This section examines the critical data requirements for the socioeconomic models, detailing the sources, availability, and quality of data parameters necessary for robust analyses. It provides an assessment of current data collection efforts and identifies gaps, ensuring the models are equipped to accurately predict the effects of NBS interventions.

3.1 Available Data Sources

The URBREATH project leverages diverse data parameters across all its models to evaluate the socioeconomic and environmental impacts of Nature-Based Solutions (NBS) in urban settings. These parameters include remote sensing indicators, socioeconomic metrics, and urban environmental data. An overview of the identified parameters are presented in the figure below.

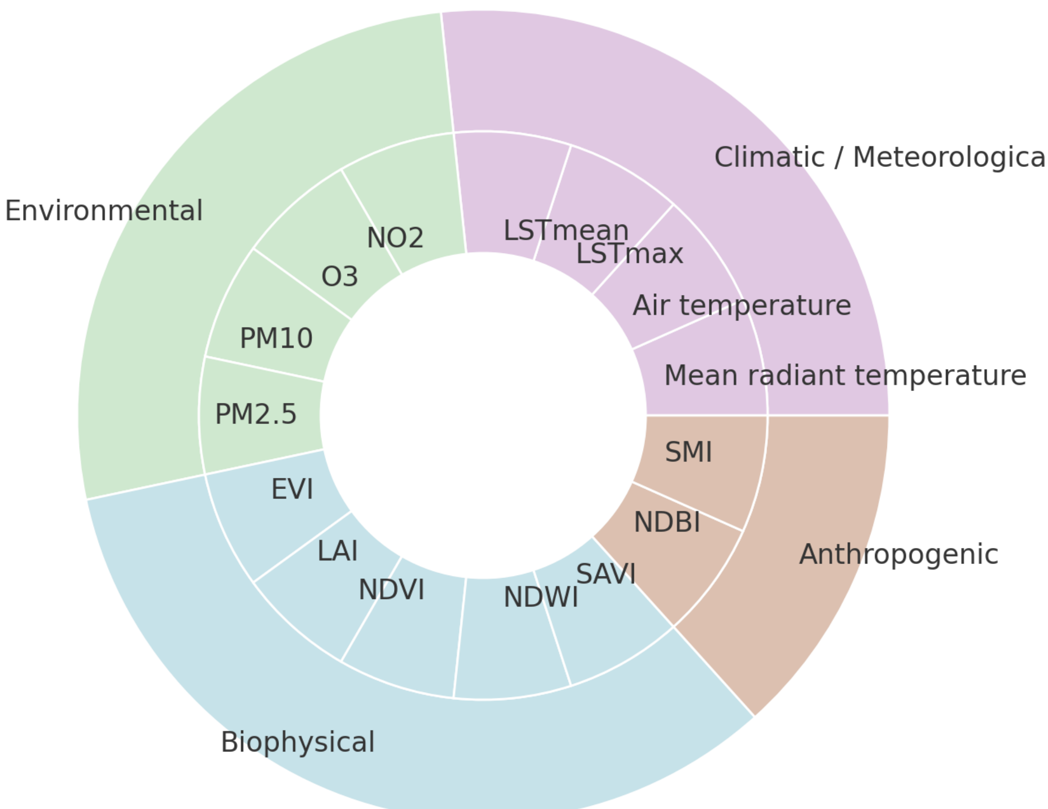


Figure 3: Taxonomy of identified remote sensing parameters to be captured

Each parameter is sourced from a combination of open repositories and contributions from end-user partners. The following data sources have been identified their sources, and the current status of data collection.

- **Normalized Difference Vegetation Index (NDVI)** is a key parameter derived from remote sensing to measure vegetation health and green space coverage. Data is sourced from MODIS and Sentinel-2 satellites, accessible via NASA's Earthdata Search and the Copernicus Open Access Hub. NDVI provides insights into the effectiveness of green infrastructure in urban environments. The data collection for NDVI is complete for pilot cities, with pipelines in place for expanding to additional regions. Ground validation from end-user partners is expected to enhance model accuracy.
- **Land Use/Land Cover (LULC)** tracks changes in urban, agricultural, and natural land uses, critical for understanding urban sprawl and the integration of NBS. This data is sourced from the ESA Climate Change Initiative and Copernicus Land Monitoring Service through the ESA Climate Data Portal and the Copernicus Open Access Hub. End-user partners contribute local zoning and municipal land-use records to complement the global data. Data collection for LULC is partially complete, with coverage for key pilot areas already acquired.
- **Air Quality (PM10, PM2.5)** data captures concentrations of airborne pollutants, which significantly affect health and urban livability. Sentinel-5P satellite data, accessed through the Copernicus Hub, provides global-scale metrics, while OpenAQ aggregates real-time local monitoring station data. Contributions from end-user partners, such as municipal sensor readings, are critical for localized analyses. Remote sensing data has been collected, while integration of local air quality data is in progress. The incorporation of the CAMS European Reanalysis Produt will also be studied, as it has the integration with local air quality data in the reanalysis step.
- **Nighttime Light Intensity** serves as a proxy for economic activity and urbanization, reflecting infrastructure use and energy consumption. It is derived from the Visible Infrared Imaging Radiometer Suite (VIIRS) via NOAA's Earth Observation Group. Nighttime light intensity data has been fully collected and preprocessed for pilot cities. Validation data from end-user partners, such as municipal economic statistics, will contextualize the findings.
- **Economic Activity** is assessed through business registries, census data, and nighttime light intensity. OpenStreetMap (OSM) provides business registry data via the Overpass API, while census and GDP data are sourced from national statistical agencies and open government platforms. Nighttime light data complements these sources as a spatial proxy for economic patterns. End-user partners provide municipal economic activity records to ensure comprehensive coverage. While nighttime light data is complete, other economic activity data is still being collected.
- **Crime Statistics** offer insights into safety levels and their effects on citizen well-being. Data is sourced from national and local open crime databases, such as UK Police Data and Open Crime Data portals. Census-based demographic data enriches the analysis by highlighting population density and socioeconomic conditions that influence crime patterns. Where open-access crime

data is unavailable, end-user partners contribute local crime reports. The availability of crime statistics is currently limited, with data acquisition in progress.

- **Property Prices and Rent Trends** reflect housing accessibility and urban equity, capturing real estate market dynamics. Open platforms like Numbeo and Zillow provide property values, transaction volumes, and rental data. National property registries and municipal surveys conducted by end-user partners offer more granular insights. Open data from real estate platforms is partially available, while detailed municipal data collection is ongoing.
- **Pedestrian Density** measures urban vibrancy and walkability, critical for evaluating the success of pedestrian-friendly interventions. IoT sensors, mobile phone location data, and OpenStreetMap provide foundational data. Telecom providers' APIs are expected to supply aggregated foot traffic data, requiring partnerships to ensure access. End-user partners contribute data from smart city pedestrian monitoring systems. This parameter is in progress, with telecom and IoT data collection at an early stage.
- **Public Transport Access** evaluates the connectivity and coverage of urban transit systems. Data is sourced from open GTFS repositories and OpenStreetMap, offering transit stop locations, service frequency, and route networks. Local transport authorities provide additional operational data. Public GTFS data is fully collected for pilot cities, while integration of local transit records is ongoing.
- **Citizen Well-being Index** quantifies quality of life improvements, encompassing parameters such as safety, green space accessibility, and housing affordability. Global indices like Numbeo and the OECD Better Life Index provide baseline data. End-user partners contribute localized survey data and metrics tailored to specific urban contexts. This parameter is partially complete, with ongoing efforts to aggregate and harmonize datasets.

A summary of all these parameters and their sources can be viewed on the table below.

Table 1: Identified sources for the socioeconomic models, & status of data collection

Data Parameter	Proposed Data Sources	Status of Data Collection
NDVI	MODIS, Sentinel-2 (via NASA's Earthdata Search and Copernicus Open Access Hub)	Collected for pilot cities, pipelines in place for others.
Land Use/Land Cover	ESA Climate Change Initiative, Copernicus Land Monitoring Service (via ESA Climate Data Portal, Copernicus Hub)	Partially complete; local zoning data from partners being integrated.
Air Quality (PM10, PM2.5)	Sentinel-5P (Copernicus Hub), OpenAQ, Municipal air quality monitoring systems	Remote sensing collected; local data integration in progress.
Nighttime Light Intensity	NOAA VIIRS (Earth Observation Group)	Collected and processed for pilot cities.
Economic Activity	OpenStreetMap (Overpass API), national statistics agencies, census data, GDP data	Nighttime light collected; census and local economic data in progress.

Crime Statistics	National crime databases (e.g., UK Police Data), local law enforcement APIs, census demographic data	Limited availability; local data collection ongoing with partners.
Property Prices and Rent Trends	Numbeo, Zillow, national property registries, municipal real estate data	Partially complete; additional municipal data required.
Pedestrian Density	IoT sensors, mobile phone location data (via telecom APIs), OpenStreetMap	In progress; early-stage collection of IoT and telecom data.
Public Transport Access	GTFS repositories, OpenStreetMap, local transit authorities	GTFS data collected; local transit data integration ongoing.
Citizen Well-being Index	Numbeo, OECD Better Life Index, end-user partner surveys	Partially complete; localized data being aggregated.

While these parameters address a large number of phenomena that affect citizen well being, and the overall socioeconomic situation for the area under study, future proposals, or the identification of additional data sources will be an ongoing process for the duration of this task and will be reported on future versions of this deliverable. Examples of the remote sensing data data captured already for Madrid city are presented below.

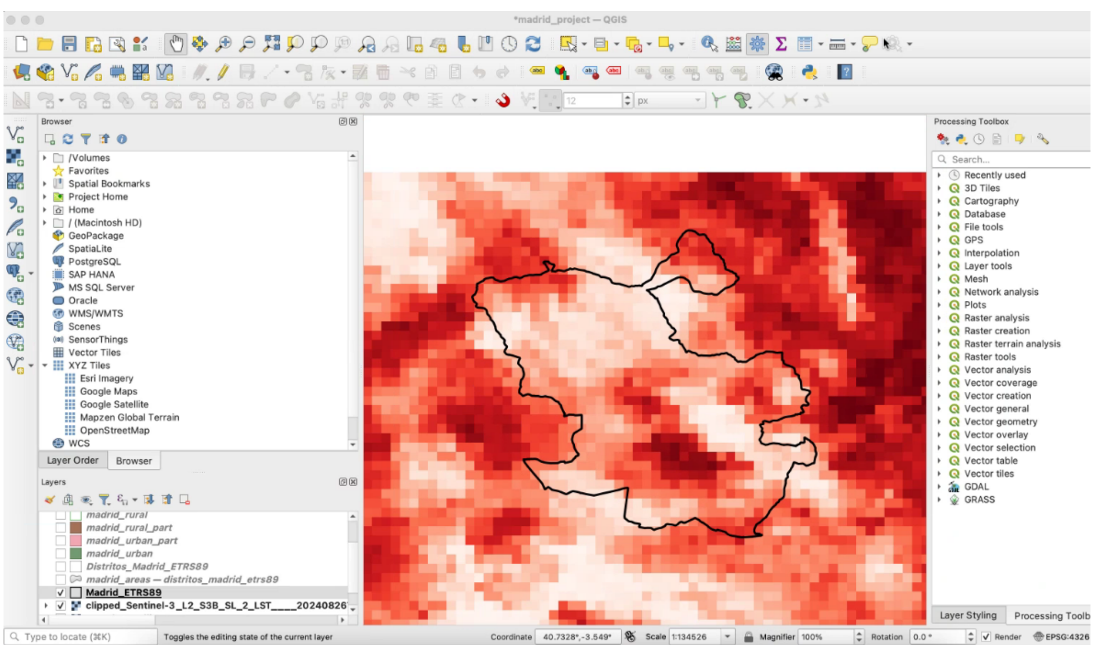


Figure 4: Land Surface Temperature for the Madrid Area (QGIS)

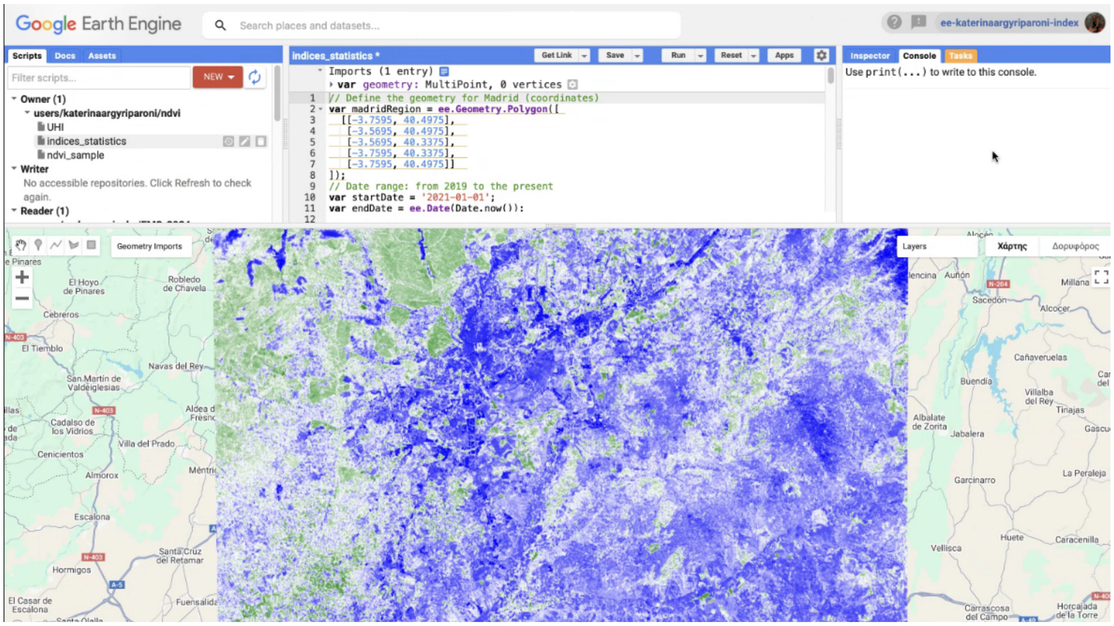


Figure 5: NDVI for the Madrid Area (Google Earth Engine).

3.2 Preliminary Input/Output Analysis

The following is a detailed input/output (I/O) analysis for the models described in the URBREATH project. The models utilize various input data parameters to predict the effects of Nature-Based Solutions (NBS) on specific urban metrics. These outputs are designed to help understand the potential changes that NBS interventions might bring to an area.

Table 2: I/O Analysis of proposed models

Model	**Inputs**	**Outputs**
Economic Activity Model	- Nighttime light intensity (NOAA VIIRS) - Census data (population density, employment rates) - Business registry data - GDP data	- Predicted changes in economic activity levels due to NBS - Identification of areas with potential economic growth or decline due to NBS effects.
Crime Statistics Model	- Geotagged crime data (law enforcement databases) - Census data (demographics, socioeconomic conditions) - Urban infrastructure data	- Predicted effects of NBS on crime rates - Identification of hotspots where NBS may reduce crime risks.
Property Prices and Rent Trends	- Real estate transaction data (Numbeo, Zillow) - Census data (income levels, population	- Predicted changes in property prices and rent trends due to NBS - Insights into affordability and housing demand shifts.

	density) - Urban environmental data	
Pedestrian Density Model	- IoT sensor and mobile phone data - Pedestrian pathway data (OpenStreetMap) - Urban infrastructure data	- Predicted changes in pedestrian density and mobility patterns due to NBS - Insights into improved walkability and foot traffic.
Public Transport Access Model	- GTFS data (transit stops, service frequency) - Census data (population density, car ownership) - Urban infrastructure data	- Predicted impacts of NBS on public transport accessibility - Evaluation of transit connectivity changes.

Each model processes relevant input data to predict how the implementation of Nature-Based Solutions will affect key urban metrics, such as economic activity, crime rates, property values, mobility, air quality, and overall well-being. These outputs provide actionable insights into the outcomes of NBS, allowing stakeholders to assess their impacts comprehensively.

4 Conclusions

This deliverable outlines the progress made in the development of socioeconomic models to evaluate the effects of Nature-Based Solutions (NBS) on urban well-being as part of the URBREATH project. The initial phase focused on defining model objectives, acquiring relevant data, and establishing the infrastructure required for modeling and analysis.

Key achievements include the collection of remote sensing data, such as NDVI and nighttime light intensity, for pilot cities, providing a foundational dataset for model development. Efforts to integrate additional socioeconomic data, such as crime statistics, property values, and mobility patterns, are ongoing, leveraging both open-access repositories and contributions from end-user partners.

The models described in this deliverable are designed to analyze specific urban metrics, including economic activity, housing affordability, mobility, and safety. The input/output analysis specifies the data needs and expected outputs of each model, ensuring alignment with project goals. However, challenges remain in acquiring high-resolution, localized data and harmonizing datasets from diverse sources. Continued collaboration with end-user partners will address these challenges and enhance data coverage and applicability. Specific effort was spent in connecting the proposed models with specific city case studies.

Future steps include the finalization of data collection, the expansion of the model pool, and the realization of the actual model training. The results of this process will be reported in the next version of this deliverable. Recognizing the critical issues of data availability and integration, we have outlined actionable plans to address these challenges. Efforts are underway to incorporate external open datasets and develop methodologies for harmonizing diverse data sources to bridge existing gaps. Additionally, we are prioritizing the development of standardized workflows to ensure seamless integration of model outputs with the URBREATH digital twin and other urban planning frameworks. These measures will enhance the robustness, scalability, and applicability of the models across diverse urban contexts.

These steps will support the development of an actionable tool that enable stakeholders to assess the potential effects of NBS interventions effectively. Finally, special focus will be given on integration, visualization, and deployment, during future phases of the project. This will ensure the models are accessible, practical, and relevant to urban planning and decision-making processes.

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