SUSTAINABLE CITY VIA TRUSTWORTHY DIGITAL TWIN: A USE CASE

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ABSTRACT

In recent years, the urbanization of modern cities has entailed the creation of new challenges in disparate applications, like infrastructure management, transportation and sustainability. In this project, we propose a way of pushing the boundaries in this sense by leveraging the power of the digital twin technology to optimize the distribution of the so-called green cells, with a focus on the use case of Bologna. The idea is to create an optimization model, which once specified the available areas fine the best n spots on the basis of a utility function.

1 Introduction

Urban environments across Europe are facing unprecedented challenges linked to climate change, biodiversity loss, pollution, and the need for more equitable access to public space. Cities like Bologna are particularly affected by urban heat islands (UHI) and urban heat waves (UHW), which intensify the effects of climate change on vulnerable populations, strain public health systems, and reduce overall quality of life. Addressing these issues requires innovative, scalable solutions that integrate environmental, social, and technological strategies.

The *European Urban Initiative – Innovative Actions (EUI-IA)* program was established to support such ambitious approaches, enabling cities to test novel ideas that have not yet been implemented elsewhere in Europe. Under this framework, the ***TALEA*** project was launched in Bologna with the goal of transforming the city's urban fabric through the creation of **TALEA Green Cells (TGCs)** – modular, adaptable green units designed to reconnect fragmented green spaces, regenerate underutilized areas, and provide climate refuges for residents [Figure 1].

The concept of green cells is rooted in the idea of micro-scale interventions that collectively produce macro-scale impacts. Each cell integrates nature-based solutions, technological tools for microclimate monitoring, and participatory co-design processes involving local communities. Together, these cells contribute to a continuous urban green infrastructure, capable of mitigating UHI effects, supporting biodiversity corridors, and enhancing citizens' health and well-being.
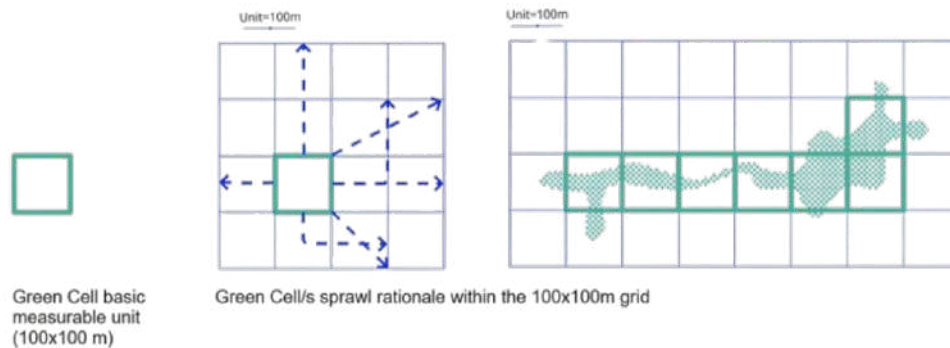

Figure 1: TALEA Green Cells (TGCs)

Beyond environmental benefits, the project emphasizes social innovation and inclusion. By targeting vulnerable areas and engaging residents directly in planning and maintenance, TALEA promotes *"green*

justice", ensuring that the ecological transition is not only sustainable but also equitable. In Bologna, three pilot zones – *Martiri-Boldrini*, *Mascarella*, and *Savena* – were selected to demonstrate different applications of the Green Cell model, from integrating green infrastructure into dense urban mobility corridors to bring back to life peripheral spaces with self-establishing vegetation.

Through these interventions, the *Green Cells project* aims to reimagine the role of green spaces in Bologna, moving from isolated parks and gardens towards a networked system of green, blue, and social infrastructure that improves citizens' welfare, fosters community engagement, and provides replicable models for cities across Europe.

This study presents a new methodology for planning the insertion of new green cells in the urban area of Bologna. Relying solely on interpretable optimization techniques – without the use of Deep Neural Networks – the approach ensures full transparency in the decision-making process. The workflow consists of:

- Collecting *open-source urban and demographic data*.
- Creating an *optimization-based, interpretable model*.
- Exploring results under *varying parameter configurations*.

By leveraging open data, the study examines how the optimal placement of green cells changes in response to factors such as population density. The interpretable nature of the method also provides urban planners with actionable, data-driven insights supported by a clear and traceable rationale.

2 Data

2.1 Data Collection

One of the crucial parts of this project is surely represented by ***data collection***. In order to insert new green areas in the city of Bologna, it is necessary to have information about the already present green space, human infrastructures and population. All of this information was gathered from `Open Data Bologna` and `Geoportale Emilia Romagna`. Both are initiatives, whose aim is to collect data for multiple purposes, according to the Italian and European directive on open data, and to make them available to the public.

In this study, the datasets listed below have been explored.

2.1.1 Land Usage Database

Uso del suolo   It is a mapping of the various uses of the territory, classified according to a hierarchical legend derived from the specifications of the European project *Corine Land Cover (CLC)*, integrated by the *Land Use Working Group of CPSG-CISIS*.
Since the 1970s, land use has been one of the most requested and widely used regional geographic datasets, both by local authorities and by professionals in the sector. The Region has repeated the mapping of the entire territory in different years, in order to identify trends and changes in its use. The databases used refer to 2020. The detailed Land Use Database is a valuable tool for understanding the territory for planning, management, and monitoring purposes. It allows for both qualitative and quantitative evaluations, comparisons with editions created in different years, and with other databases.

2.1.2 Green Data

Verde in gestione   It comprises all green units maintained by the Municipality of Bologna, including a wide range of types.

Verde privato   It includes the mapping of green areas within the urbanized territory, excluding public green spaces under maintenance. This dataset, together with the *"verde in gestione"* one constitute the two main sources of green spaces in the area of Bologna.

Alberi in manutenzione   It contains the information about the type of tree and the coordinates of all the trees planted in the city of Bologna. This dataset has been used to have a more accurate information about the green spaces already available. There are some areas in which we have no parks, nor gardens but there are trees, which are as important for heating and climate factors.
The dataset only contains the coordinates of each trees. Estimating the areas occupied by each of them was not straightforward and involved a too big approximation. Therefore, it has been taken the decision

to count all the trees which do not fall inside a green space and use that count as a factor to increase the green impact.

Aree boschive   It represents the area of land covered by tree and/or shrub and/or bush vegetation of forest species, whether of natural or artificial origin, at any stage of development, with a density greater than 10%. It has been used to enlarge the amount of green space including the forest areas.

Aree fluviali   It includes the areas covered by water, including rivers, riverbeds and lakes. What are called in literature *"blue cells"* have been considered at the same level of the green spaces. Indeed, it has been decided to collapse the datasets, since there were no significant reasons to differentiate between the green and blue, given the absence of a large amount of waterfall in the Bologna Municipality.

2.1.3   Human Infrastructure Data

Edifici particellari   It contains the list of buildings with parcel details extracted from the Municipal Technical Map and aggregated with public cadastral information (Sheet/Parcel) from the cadastral, available through the WMS service of the Revenue Agency for consultation of the cadastral maps.

Aree stradali   Map of the street areas in the city of Bologna, including all the different types of roads, parking areas and squares, enriched with descriptions about the layout.

Figure 2: a) Dark Green: *"Verde in gestione"*; b) Light Green: *"Verde privato"*; c) Yellow: *"Aree stradali"*; d) Brown: *"Edifici particellari"*.

2.1.4   Statistical Data

Aree statistiche   Division of the municipal territory into *90 statistical areas*. It meets the need of a grid for data analytics in a more detailed way than the traditional division of Bologna into districts or zones, and at the same time sufficiently concise compared to the highly fragmented structure of census sections.

Popolazione per area statistica   It contains the population density of Bologna, computed at different levels of granularity. From the most detailed to the least detailed, we have:

- *districts*, the main administrative divisions of the city;

- *city zones*, further subdivisions of the districts;

- *statistical areas*, the smallest geographic subdivisions used for data analytics.

3

Urban Heat Island analysis   It is part of the `TALEA` project and analyses the Urban Heat Island (UHI) effects over the city of Bologna in the summer of 2024. It is a collection of multiple indexes, used in literature for geospatial analytics and computed using open satellite data from **Landsat 8/9** and **MODIS**. In this study, two indexes in particular have been widely used to discriminate the areas marked as available to build green space on top of them:

- *Normalized Difference Vegetation Index (NDVI)*, which models directly the quantity and the quality of green areas on the land surface;
- *Urban Heat Exposure Index (UHEI)*, which shows how heat accumulates and persists in different areas of the city and is a composition of other indexes, according to the formula:

$$LST^1 + (1 - NDVI) + (1 - Albedo^2) \tag{1}$$

2.2   Data preprocessing

The afore-mentioned data are ***not ready to use***, since they are not thought to be used in an algorithmic contest. They lack of a usable structure and there is no unique dataset for the same data, leading to multiple duplicates. Furthermore, some geospatial information are corrupted and need to be refined, as long as some missing data, requiring modification which lead to non-exact solutions.

To overcome these problems, a heavy processing step is required, meaning that they need to be reorganized and processed in order to extrapolate the relevant information. One of the most useful tools to work with geospatial data is **QGIS**, which offers also a python interface. Furthermore, many datasets present overlapping information which should not be duplicated.

To understand the preprocessing steps, let's define some approximation used during the definition of this study. To place new green areas it is important to understand where to place them. For this purpose, it has been defined the concept of **free space**.

> The ***free space*** is the remaining space in the city, once you remove buildings, roads, all the human infrastructure and the green space. In most of the cases, it represents the yard court of the buildings.

Furthermore, it has been hypothesized that the roads are places where new green areas can be inserted. Of course, this is an approximation, but to make it as realistic as possible it has been decided to exclude all the squares and the highways, where it would have been more complex (or even impossible) to build upon.

The steps done during preprocessing are the followings:

- The **green datasets** contents have been aggregated under a unique dataset, avoiding duplicates. In this process, it has been found that the dataset *"Verde in gestione"* contains some corrupted geospatial information, causing errors in the union. Therefore, we performed a geometry fixing operation, which aims to connect this "holes", avoiding the aforementioned error;
- The **roads dataset** also contains squares and highways in it. Since no dataset for squares is available, they have been recognized to belong to the attribute *'Tronco di intersezione tra strade a raso'*, which has been properly filtered to delete them. Empirically, it has been found that setting a threshold which removes all the elements who's area is bigger than $7500 \ m^2$ is a good trade-off. Instead, the highways are contained in the land usage dataset under the feature *'Autostrade e superstrade'*. Therefore, a difference operation has been performed between the dataset coming from the square deletion and the land usage one;
- The **free space** has been computed by selecting the residential areas from the land usage dataset, under the attributes *'Tessuto residenziale compatto e denso'*, *'Tessuto residenziale urbano'*, *'Tessuto residenziale rado'*. They have been recognized as the most appropriate surface areas for hosting new green cells, which do not affect commercial spaces and parking lots. From this base, the deletion previously described has been performed, removing the green space, the roads and the buildings;
- The **cityscape of Bologna** has been extracted from the dataset *"Aree Statistiche"*. However, some areas lack of information about the green space and buildings, so it has been decided to remove them. The final usable area is described in Figure 3.

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[1]*Land Surface Temperature (LST)* measures the Earth's surface temperature during the day.
[2]*Albedo* measures how much the land surface reflects the light, helping to identify the areas that retain the more solar energy.

- Once the area of work has been delimited, a **grid of cells** with dimensions $100m \times 100m$ has been created to define where to insert the new *TGCs*.
- The **UHEI data** have been collected under different specifications and with cells of different sizes with respect to the grid just described. In order to adapt them to this study, an average weighted according to their intersection area with this project's grid has been computed.

The **final unified dataset**, showed in image 3, used by the optimization model is composed of all the cells of the grid, where each of them is enriched by the following data:

- *UHEI*
- *NDVI*
- *green space area*
- *buildings area*
- *road space area*
- *free space area*
- *number of free space fragments*
- *number of trees*
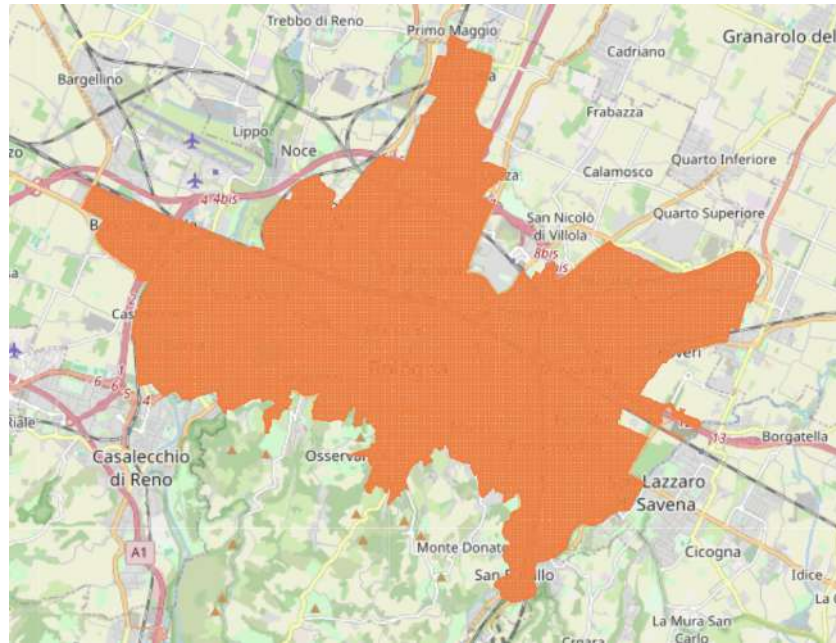
Figure 3: Final unified dataset

2.2.1 Macro-dataset

This unified dataset only represents information under a *micro-scale* point of view. It is also important to have a *macro-scale* view, represented by the dataset *"aree_statistiche_macro"*, which contains all the used statistical areas with information about:

- **population density**, stored in *"densità-per-area-statistica"* and obtained from the division between the population from the dataset *"popolazione-per-area-statistica"* and the area itself;
- **green space**, contained in *"aree_statistiche_stat"*, resulting from the aggregation of the green space present in each area.
- the average **UHEI** of the cells contained in the statistical areas.

As shown in the image 4, the city center, Pontevecchio and Bolognina exhibit the highest need of new green areas, due to low presence of green space, high population density and high UHEI factors. Moving toward the suburbs, population density gradually decreases. Unsurprisingly, the areas with the highest concentration of green space are the Colli.
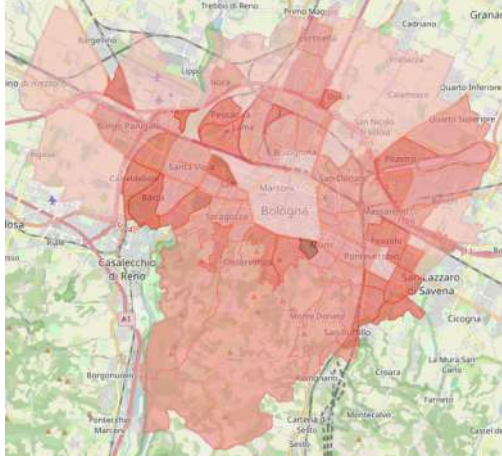
(a) Macro visualization of green factor. The lighter is the color the less green is there.
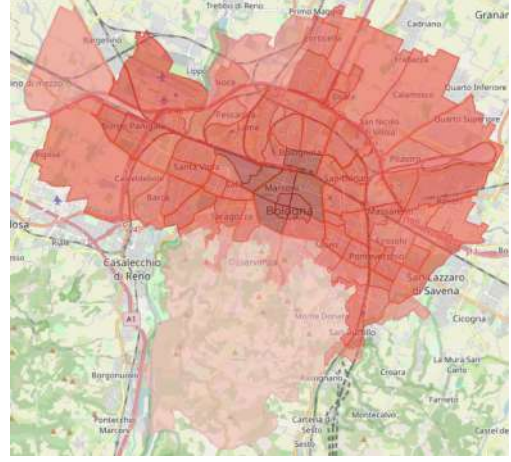
(b) Macro visualization of UHEI factor. The darker is the color the higher is the UHEI and the environmental risk, so the higher is the necessity of new green areas.

Figure 4: Macro visualization

3 Model

The problem has been formalized as a *Constraint Optimization Problem (COP)* using **Minizinc** and run using the Mixed Integer Programming (MIP) solver **HiGHS**. The model is built on the objective of finding the n best cells to place a TGC, that maximize a utility function. The utility function for each cell i_{th} is defined as follows:

$$utility_i = macro\_factor_i * micro\_factor_i \tag{2}$$

The model assigns the amount of green space to be placed on the road and the yard area - $street\_cells$ and $yard\_cells$ respectively. Furthermore, a *binarization* of the variables is performed to restrict the number of placements, so that the total number of new cells, whose value is different from zero, is less than or equal to n.

Multiple utility functions have been developed by changing the *micro_factor*, while the *macro_factor* is in common for all of them.

3.1 Macro factor

The macro factor is formulated as follows:

$$\begin{aligned} \text{macro\_factor}_i = {} & density\_param * \text{density\_factor}_i \\ & + green\_param * \text{green\_factor}_i \\ & + uhei\_param * \text{uhei\_factor} \end{aligned} \tag{3}$$

The **macro_factor** acts as a multiplicative factor. It is computed with the green space, the population density and the UHEI of the whole statistical area where the actual cell is. In particular, it increases proportionally with respect to the population density and UHEI and inversely with respect to the green space. The parameters $density\_param$, $green\_param$ and $uhei\_param$ define a weighted average, each of them is thought to be in the range [0, 1] and their sum to be equal to 1.

3.2 Micro factor

In this section are listed, and explained, all the formulations done for the micro factor.

The common elements composing all the utility functions are the followings:

- **street_cells**: streets area inside the cell. With the parameter $\beta_{streets}$, we can regulate which percentage of the street is available for the placement of a TGC;

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- **yard_cells**: yard area inside the cell. The placement of a TGC here is limited by the free space (ext_space in the model) and its impact of the utility function is regulated by the parameter α_{yard};
- **num_areas**: number of yard_cells inside a cell. The higher it is, the more the yard area is fragmented and the lower is the utility;
- **green_space**: amount of green area already present in the cell. The utility grows inversely to this value;
- **num_trees**: number of trees in the cell (same behaviour as the green space).

All the elements in the utility function are normalized on the basis of their maximum value, in a way that each factor influences the utility equally.

3.2.1 Difference utility

The first utility is composed as the available space in the cell (*yard_cells* and *street_cells*) minus the elements which decreases the cells's utility (*num_areas*, *green_space*, *num_trees*, *uhei*).

It's a really simple and intuitive function, which can be used as a comparison with the results for the others.

$$\text{macro\_factor}_i \times (\ \alpha_{yard} \cdot \text{yard\_cells}_i + \beta_{streets} \cdot \text{street\_cells}_i$$
$$- \text{num\_areas}_i - \text{green\_space}_i - \text{num\_trees}_i - \text{uhei}_i) \tag{4}$$

3.2.2 Inverse UHEI

This utility function is based on the ***Inverse UHEI (IUHEI)***, that spans in the positive real values' range. As expectable, contrarily to the UHEI, the lower is the index value, the higher is the heat island risk and it means also that the lower is the amount of vegetation present.

$$IUHEI_i = max(UHEI) - UHEI_i \tag{5}$$

The idea is to formalize with a mathematical relation the impact of the *Fractional Vegetation Cover (FVC)* - limited to the new TGCs - on the IUHEI. The problem is that recent studies from *Iglesia Martinez and Labib (2023)* proved that there is not an absolute formula that works universally over the globe. Indexes like the NDVI and so the UHEI are computed through spectral reflectance measurements from satellites, which are heavily influenced by atmospheric conditions. In addition, the observed distribution of those indexes is dependent on the area of interest (AOI), specifically on its tree canopy and vegetation type, with a non-linear relation.

Therefore, the estimated impact of the new TGCs on the utility has been normalized according to the observed data, putting attention on excluding eventual outliers in the data. The factors below have been used:

- **inverse_uhei_95p**, 95th percentile of the IUHEI values, identifying dense vegetation;
- **inverse_uhei_5p**, 5th percentile of the IUHEI values, identifying bare soil/urban environment.

The resulting utility is defined in the formula below, where the assumption is that once the normalization is applied, the impact of *street_space* and *yard_space* is **linear**:

$$\text{macro\_factor}_i \times \frac{(\alpha_{yard} \cdot \text{yard\_cells}_i + \beta_{streets} \cdot \text{street\_cells}_i)}{\text{full\_space}_i}$$
$$\times \frac{(\text{inverse\_uhei\_95p} - \text{inverse\_uhei\_5p})}{\text{num\_areas}_i + \text{green\_space}_i + \text{num\_trees}_i} \tag{6}$$

3.2.3 NDVI

This utility function is based on the same criteria explained in section Inverse UHEI, with the difference that in this case the index used is the ***NDVI***, which is more strictly correlated to the green space. In general, it spans in the range [-1, 1] where negative values stand for urbanized areas and positive ones for vegetated zones. However, the data available for this study were normalized in the range [0, 0.8].

In order to reconstruct the impact on the NDVI given by new TGCs, an interesting inspiration comes from *Carlson and Ripley (1997)*. This study highlights the need of a measure of the NDVI as if it computed at the surface, obtained by scaling the observed values according to the AOI. Together with *Choudhury et al. (1994)* and *Gillies and Carlson (1995)*, they also prove the existence of a square root relation between the *Fractional Vegetation Cover FVC* and the *scaled NDVI N°*, formalized as follows:

$$FVC = N^{\circ 2} = \left(\frac{NDVI - NDVI_0}{NDVI_S - NDVI_0} \right)^2 \tag{7}$$

$NDVI_0$ and $NDVI_S$ correspond to the values of the NDVI for bare soil and a surface with a FVC of 100%, respectively.

Given the previous statements, the *micro_factor* in the utility function defines the *increment in the NDVI obtained by inserting the new TGCs* and contains:

- **ndvi_norm_max**, corresponding to $NDVI_S$ and set to 0.8;
- **ndvi_norm_min**, corresponding to $NDVI_0$ and set to 0;
- **ndvi**, containing the current values of the NDVI, which models the existing green and substitutes the sum green_space + num_trees of the previous utility functions.

It is a square root relation, but since Minizinc struggles with quadratic constraints, a *first order linear approximation* has been performed to obtain the final formula:

$$\text{macro\_factor}_i \times \frac{(0.5 * FVC + 0.5) \times (\text{ndvi\_norm\_max} - \text{ndvi\_norm\_min}) + \text{ndvi\_norm\_min}}{\text{ndvi}_i + \text{num\_areas}_i} \tag{8}$$

$$FVC = \frac{\alpha_{yard} \cdot \text{yard\_cells}_i + \beta_{streets} \cdot \text{street\_cells}_i}{\text{full\_space}_i}$$

4   Results

The optimization model developed exposes multiple hyperparameters, which open the doors to multiple experimentations and comparisons on each utility function.

In this section we are going to examine how the models presented in section 3 behave under different macro factor's parameter values. In the **equal-weighted** configuration all the macro factors have the same importance, while in the others one factor (**green**, **density**, **uhei**) has a bigger weight with respect to the others.

For all the experiments it has been decided to set at 100 the maximum number of cells to build. Only the most relevant experiments on the Bologna hallway have been illustrated, so as the performed analysis.
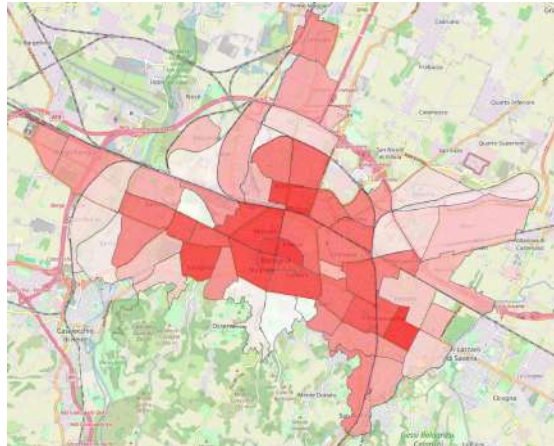

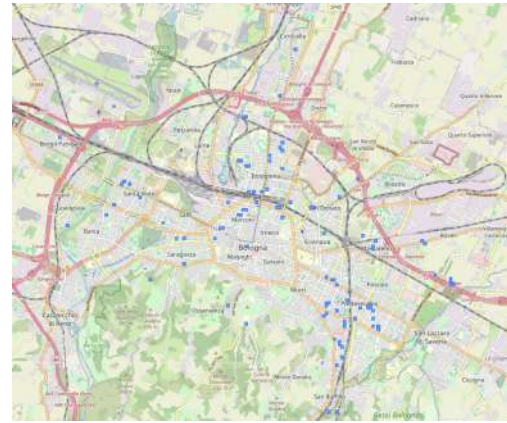Figure 5: Macro factor utility visualization with equal weights between parameters

4.1 Equal-weighted configuration

In this experiment equal weights have been assigned to the different elements of the macro factor.

Since no preference has been given to those elements, the models tend to insert the output cells over the inner urbanized area of Bologna. Overall, statistical areas like the *center*, *"Pontevecchio"* and *"Bolognina"* are identified as preferable for new placements, with the difference and NDVI models that are more biased toward them with respect to the IUHEI one, at first glance.

(a) difference model

(b) inverse uhei model
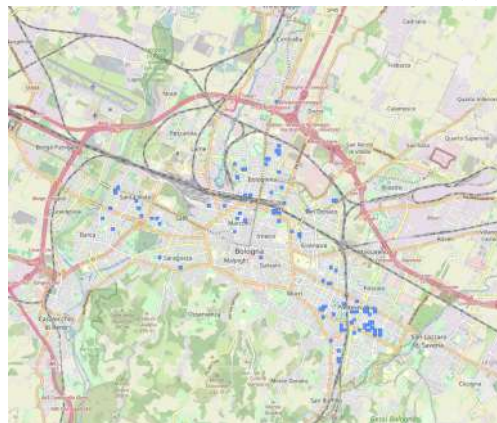
(c) ndvi model

Figure 6: Equal-weighted config
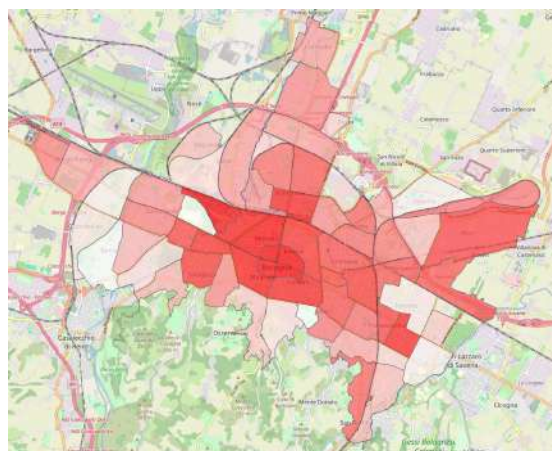
Figure 7: Macro factor utility visualization boosting the green factor

4.2 Green enhanced configuration

The green enhanced configuration is set with a much greater weight for the green factor with respect to the others. The distribution of the resulting macro factor in this case shows the areas with the lower amount of green spaces, not surprisingly, while increasing the values in the suburbs, especially in the east part of the map.
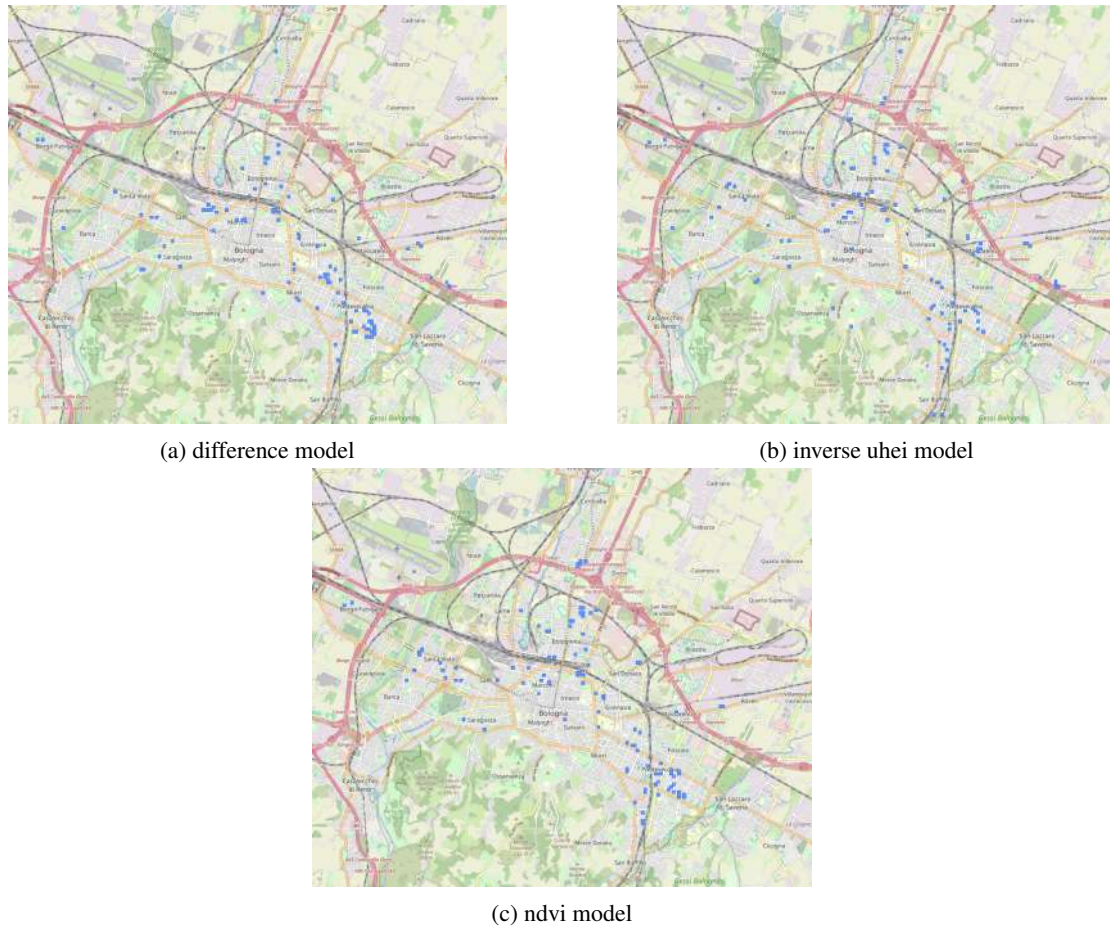

(a) difference model

(b) inverse uhei model

(c) ndvi model

Figure 8: Green enhanced config

The results for all the models above show a widespread distribution of the new TGCs over the entire Bologna cityscape, reflecting the heatmap of the macro factor values in Figure 7. The point to underline in this case is that this configuration balances the macro factors over the statistical areas, reducing the differences between highly populated urban areas and more industrialized zones like *"Roveri"* or *"Borgo Panigale"* from the point of view of the green impact.

4.3 Population density enhanced configuration

The density enhanced configuration boosts the density factor with respect to the others. Not surprisingly, as showed in Figure 9, the areas with the higher macro factor are the most populated statistical areas. In particular, the most density populated one is *"Pontevecchio"*, but also *"Saragozza"*, *"Bolognina"* and the *city center*.

By comparing the macro_factor heatmap with the equally distributed one, the population density shows a strong impact on the macro values even when the weights are equally distributed. Indeed, looking at the models' cell placement, the observed behaviours are similar in the two cases. What emerges here is a high concentration of the new TGCs in the statistical areas previously mentioned, especially in the *"Pointevecchio"* district.

The IUHEI is the only model whose results are more spread around the map, giving more importance also to the *city center* and *"Bolognina"* statistical areas.
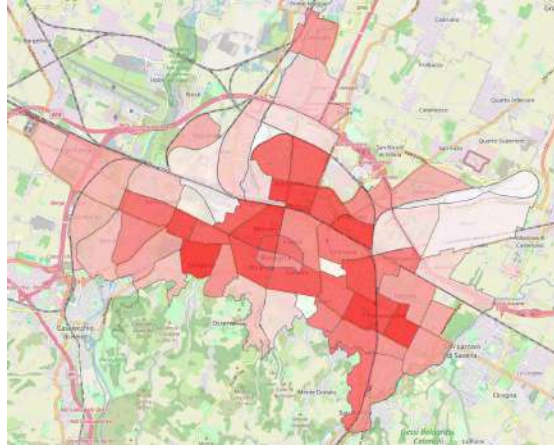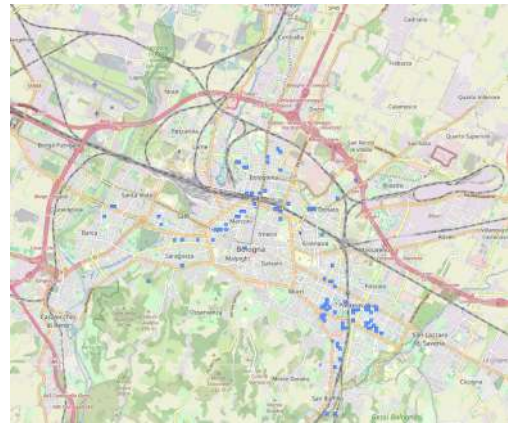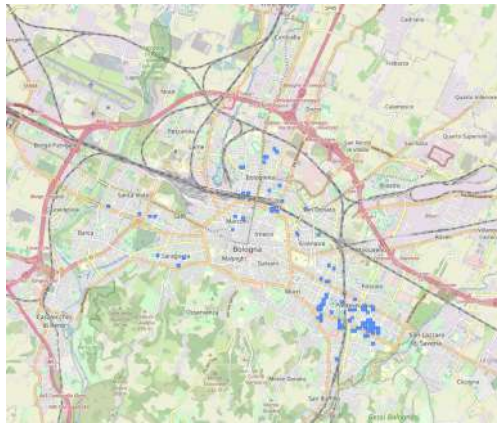
Figure 9: Macro factor utility visualization boosting the population density factor

(a) difference model

(b) inverse uhei model

(c) ndvi model

Figure 10: Density enhanced config

4.4 UHEI enhanced configuration

This is probably the configuration which gives more importance to the peripheral areas, Figure 11. The uhei factor is the fairest ones, as it can be viewed as a summary of multiple information, as described in Statistical Data.

This behaviour is reflected also in the models results. Areas like *"Borgo Panigale"*, *"Corticella"* and *"Roveri"*, almost ignored in the previous configurations assume a much higher importance. The NDVI model also strongly focus on *"Santa Viola"* area, while completely removing cells from *"Saragozza"*.
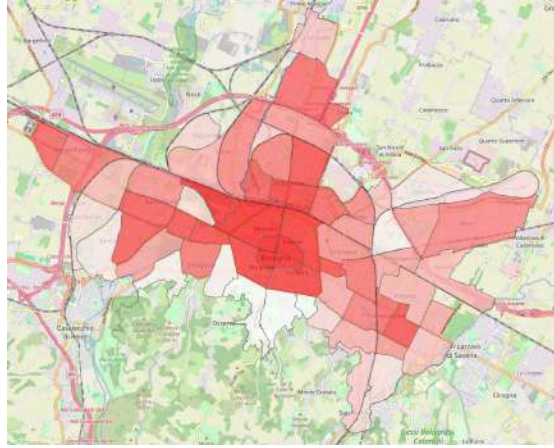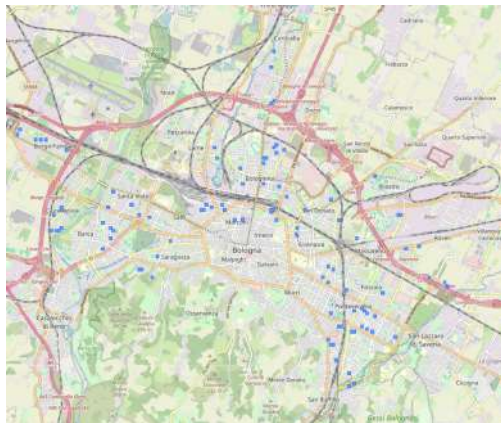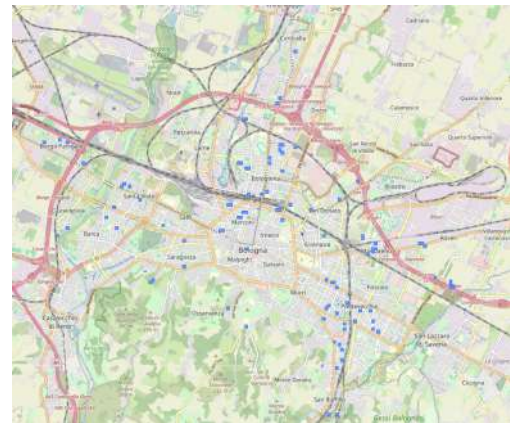
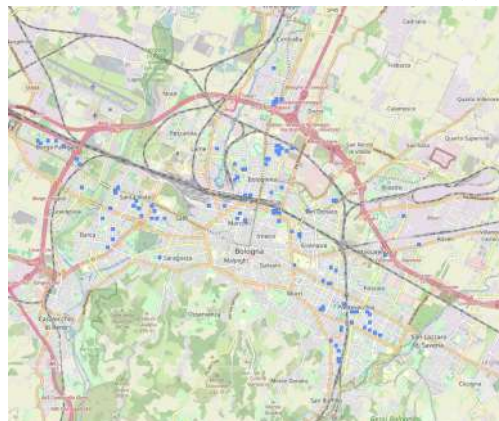Figure 11: Macro factor utility visualization boosting the uhei factor

This behaviour is due to the nature of the NDVI index, which models more accurately the amount of green space, which is already noticeable in the entire *"Saragozza"* district, as confirmed also by previous observations.

(a) difference model

(b) inverse uhei model

(c) ndvi model

Figure 12: Uhei config

5 Conclusions

The section Results showed how the macro-factor utility strongly influences the selection of statistical areas where to place new green cells. Indeed, comparing the same model with a different *macro-factor* the cell placement heavily differs.

Since there is not a quantitative benchmark to evaluate the performance of each model, a qualitative analysis has been conducted. Areas like *"Martiri-Boldrini"*, *"Via Milazzo"* and *"Mascarella"* have been identified by human architectural experts as pilot areas and designed as the most likely to undergo intervention. Those areas are selected by the models in multiple parameters configurations, symptom that although the approximations, the models still maintain realism in the results.

The approximations introduced during data preprocessing, along with the absence of key information such as budget, the topology of new green cells, and the structure of paths connecting green areas, resulted in simplified model constraints. This, in turn, could limit the real-world feasibility of the proposed new green areas, but open the way to more in-depth studies.

6 Engineering Approach

The entire project, along with its environment, has been containerized using ***Docker***. This is noteworthy because it makes the entire study fully reproducible and easy to share.

Reproducibility was a significant challenge in this project due to the use of ***QGIS*** and ***PyQGIS***. PyQGIS cannot be easily installed in a local environment via common package managers such as pip or conda. Instead, you must install the QGIS application on your local machine and then manually configure the path to the Python packages inside the application, which are OS-dependent. This process reduces the shareability of the code and imposes a significant barrier for end users wishing to run the project. By using a QGIS-based Docker image within the container, this limitation has been completely overcome.

Additionally, this project relies on spatial data, which is best understood when visualized – especially for transformation processes and results. Displaying such data in tables often leads to ambiguity and poor clarity. To eliminate the need for a third-party application, a simple ***Graphical User Interface (GUI)*** has been developed, which currently allows the visualization of results and data in GeoJSON format.

7 Future Work

The current study employed simplified approximations and omitted several details due to limited data availability. Future research should address these limitations by incorporating more comprehensive datasets, particularly with respect to *budget constraints*, which are critical in realistic urban planning scenarios. Additionally, expanding the geographical scope to include currently excluded city areas — omitted due to insufficient or outdated information — would improve the robustness of the analysis.

The present model assumed *no restrictions on construction sites*. However, this assumption is unrealistic in practice. Subsequent work should account for *technical and legal constraints*, including the challenges of building on existing road infrastructure and the significant bureaucratic and legal complexities involved in expropriating private property.

Further refinements could be achieved by integrating additional variables such as *socio-economic conditions*, *accessibility to public transport nodes* (e.g., bus and metro stops), *flood risk*, and *prevailing wind patterns*. Incorporating these elements would allow for a more accurate and holistic representation of urban development scenarios.

On the technological side, future developments will focus on enhancing the Graphical User Interface (GUI) to enable:

- *Real-time computation* of updated results from incoming data streams;
- *Multi-format data compatibility* to support diverse sources;
- *Dynamic scenario simulations* that allow planners to vary budgetary, zoning, and environmental parameters interactively;
- *Advanced visualization tools* to facilitate intuitive exploration of spatial and temporal patterns.

These enhancements aim to provide urban planners and policymakers with a more realistic, data-driven, and adaptable decision-support framework.

References

Carlson, Toby and David Ripley (Dec. 1997). "On the Relation between NDVI, Fractional Vegetation Cover, and Leaf Area Index". In: *Remote Sensing of Environment* 62, pp. 241–252. DOI: 10.1016/S0034-4257(97)00104-1.

Choudhury, B et al. (Oct. 1994). "Relations between evaporation coefficients and vegetation indices studied by model simulations". en. In: *Remote Sensing of Environment* 50.1, pp. 1–17. DOI: 10.1016/0034-4257(94)90090-6. URL: http://dx.doi.org/10.1016/0034-4257(94)90090-6.

Gillies, Robert and Toby Carlson (Apr. 1995). "Thermal Remote Sensing of Surface Soil Water Content With Partial Vegetation Cover for Incorporation Into Climate Models". In: *Journal of Applied Meteorology* 34. DOI: 10.1175/1520-0450(1995)034<0745:TRSOSS>2.0.CO;2.

Iglesia Martinez, Alex de la and S.M. Labib (2023). "Demystifying normalized difference vegetation index (NDVI) for greenness exposure assessments and policy interventions in urban greening". In: *Environmental Research* 220, p. 115155. ISSN: 0013-9351. DOI: https://doi.org/10.1016/j.envres.2022.115155. URL: https://www.sciencedirect.com/science/article/pii/S0013935122024823.