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Abstract

With the continuous rise of global urbanization, city planners and policymakers are increasingly concerned with urban heat islands (UHI), which are metropolitan areas that are significantly warmer than their surrounding rural areas. We address the United Nation's Sustainable Development Goal 11 "Sustainable Cities and Communities," and we design and develop a decision support system (DSS), which will help city planners and policymakers to overcome economic barriers to reach environmental sustainability goals.

Keywords

Urban heat, green information systems, decision support, morphological analysis, policy making.

Introduction

The impacts of climate change on natural hazards such as floods, droughts, and wildfires pose a critical threat to global stability, which are exacerbated by the urban heat island (UHI) effect (Levermore et al. 2018; Mohajerani et al. 2017). City planners are increasingly concerned with UHI, which are metropolitan areas that can cause urban temperatures to be between 2 and 12 degrees Celsius higher than surrounding rural areas (Gunawardena et al. 2017; Li et al. 2019; Stone et al. 2012). The UHI effect is strongest in densely built-up areas (Ho et al. 2016), where rapid urbanization leads to the vulnerability of cities concerning challenges like population growth and environmental catastrophes (Selby and Desouza 2019).

We develop and discuss a tool in the form of a decision support system (DSS), which optimizes an area for the city planner target group regarding an optimal balance between economic and ecological factors. Thus, the DSS mainly contains an optimization model that assigns a selection of building and vegetation options to the corresponding location. A morphological analysis is carried out for the tool development in order to identify primary influencing factors from the literature and subsequently integrate them into the model. The tool provides a solution prototype that will help city planners to make informed decisions with limited budgets and resources designing and optimizing urban districts.

We develop an optimization model in two different variants since we consider the optimal balance as a trade-off relationship, because the economic interests are maximized by accepting a maximum UHI effect. Accordingly, the first model contains a revenue maximization while maintaining a maximum limit for the UHI intensity. Revenue can be defined as the amount in monetary units that city planners receive in cooperation with the policymakers selling land to developers who invest in buildings in the respective areas afterward. We design the second model to minimize the UHI effect while maintaining a minimum revenue limit. Both models are relevant for optimization due to different individual interests of the decision-makers. The analyst can choose between both models as part of the DSS, which consists of input, the model, and a visualization of the results as well as a corresponding graphical user interface (GUI). Our research question is:

How can city planners and policymakers maximize revenue while limiting urban heat island intensity?

We proceed as follows: First, we outline a morphological analysis in order to identify relevant aspects for a first optimization model iteration. Then, we discuss the optimization model in two variants: revenue maximization and UHI effect minimization. Then, we describe the overall DSS structure and show a first version of a DSS GUI mock-up. Finally, a discussion and conclusions follow.

Morphological Analysis

With regard to the UHI effect, it is important to consider the design and energy assessments of buildings in urban areas due to their storage and release of heat energy, which affects thermal comfort within occupied buildings, as well as increased energy needs during building operations (Aghniaey et al. 2018; Lawrence et al. 2016; Levermore et al. 2018; Mohajerani et al. 2017). In order to break this complex system of urban infrastructures into parts that are critical for the mitigation of the UHI effect, we draw on a morphological box that allows to explore possible solutions to multi-dimensional, non-quantified complex problems (Zwicky 1969). To categorize the parameters of the morphological box, we use the three eco-goals of *eco-efficiency*, *eco-equity*, and *eco-effectiveness* (Dyllick and Hockerts 2002; Watson et al. 2010) as interventions to mitigate the UHI effect, and include economic and environmental outcomes, which are influenced by the interventions (see Table 1).

Table 1. Specified Morphological Box with Model Integration

<table>
<tr><td>Eco-efficient interventions</td><td colspan="2">Reduction of building density and height</td><td colspan="4">Vegetation (green spaces, green roofs, tree planting)</td><td colspan="2">Albedo (light-colored building envelope)</td></tr>
<tr><td>Eco-equity interventions</td><td colspan="2">Low income neighborhoods</td><td colspan="4">Medium income neighborhoods</td><td colspan="2">High income neighborhoods</td></tr>
<tr><td>Eco-effective interventions</td><td colspan="2">Cradle-to-cradle (recyclable construction materials in a closed loop system)</td><td colspan="4">Renewable energy (solar panel implementation on roofs)</td><td colspan="2">Passive building design (natural lighting and ventilation)</td></tr>
<tr><td>Economic outcomes</td><td colspan="4">Revenue</td><td colspan="4">Timeframe</td></tr>
<tr><td>Environmental outcomes</td><td>Temperature</td><td colspan="2">Wind intensity</td><td colspan="2">Urban canyon effect</td><td colspan="2">Energy consumption</td><td>Greenhouse gas emission</td></tr>
</table>

Notes: influencing factors marked grey are included in the optimization model; light grey indicates that the reduction of building density is included but not the reduction of building height.

The goal of *eco-efficiency* is to reduce the ecological footprint of existing environmentally harmful solutions (Huppes and Ishikawa 2005; vom Brocke et al. 2013; Watson et al. 2011). In our case, we suggest that a reduction of the density and height of buildings (Duan et al. 2019), an increase of the cultivation of vegetation (Kamruzzaman et al. 2018), and an increase of the use of high-albedo materials (Deilami et al. 2018) will lead to a reduction of temperature and other environmental harmful factors. *Eco-equity* refers to a fair distribution of resources in sustainable development (Watson et al. 2010), for which we propose neighborhood income as a relevant indicator because of its correlation with building density and vegetation (Vargo et al. 2016; Yigitcanlar et al. 2015; Zhu and Zhang 2008). The ultimate solution for ecological challenges is considered to be *eco-effectiveness*, which "aims to stop contamination and depletion, instead of only slowing down their speed, by directing individual and organizational attention to the underlying and fundamental factors of environmental problems to make possible long-term prosperity through a fundamental redesign of the system" (Chen et al. 2008, p. 195). In a city planning context, we consider the cradle-to-cradle approach (Ingrao et al. 2018; Ioppolo et al. 2019), where construction materials are used for buildings that are recyclable in a closed loop system (Ankrah et al. 2013). We further consider the generation of renewable energy facilitated by buildings such as embedding photovoltaic cells in sun facing surfaces (Masson et al. 2014), and the design of buildings that use natural lighting (Watson et al. 2010).

In addition to revenue, economic interventions also include a timeframe. Timeframe describes the period in which the city planner aims to complete the project, which can influence the other factors as well as the UHI intensity. A possible integration of the timeframe component would be the implementation of a discounted cash flow model. Since the buildings on the surfaces influence the microclimatic conditions with respect to the wind flow, this aspect is also included in the morphological box within the environmental outcomes. The urban canyon effect describes the arrangement of tall buildings in a row. The geographical location of tall buildings, for example, influences the heat distribution of buildings, which is why energy consumption is also affected. Energy consumption is closely linked to UHI intensity, since heat islands in cities, for example, result in a higher energy requirement for air conditioning. If the temperatures in cities rise and thus the energy demand for air conditioning also increases, this has consequences for greenhouse gas emissions. These emissions are affected by a variety of influencing factors, which is why they are arranged within the environmental outcomes in the morphological box.

After the summary of relevant factors contributing to the UHI effect within the morphological box, it is necessary to determine which factors are feasible for an initial step regarding the integration into the optimization model and the DSS.

Optimization Model

The optimization model serves as a decision support for city planners by populating a map of a district with the optimal balance between the built-up area and vegetation in terms of the trade-off relationship between revenue and UHI intensity as defined within the research question. Since city planners may have different requirements due to starting situations when using the DSS, we propose different interests and scenarios in the model when making decisions. By setting up land-use decisions, city planners are faced with a trade-off situation between maximum revenue and the ecological aspects of rising temperatures due to the UHI effect. Since revenue is only maximized with maximum utilization of the area in terms of the amount of buildings, this leads at the same time to minimum vegetation on the map and thus to a maximum UHI effect. This is a conflict of interest in multi-objective optimization. To optimize the two objectives within the trade-off, one of the two objective functions must be transformed into another constraint. For this reason, it seems reasonable to offer the optimization model in two variants. On the one hand, for the UHI intensity minimization of the whole map (under the constraint of a minimum revenue which has to be exceeded by the model), and on the other hand, for a given UHI level to maximize the revenue for the sale of the land areas. Since the economic efficiency of city planning is at the core of the decision, it must be recognized within the framework of the model.

The decision, which of the two model variants is used for optimization, depends on the individual objective of the decision maker. All in all, despite the importance of ecological influencing factors, we focus on a city suburb, in which houses are planned to be built for settlement due to the demand of residential space. Because of this increase of the built-up area and therefore reduction of the vegetation area, it is crucial to satisfy the demand for residents and still maintain the ecological effect concerning an urban temperature increase in balance. For the demand of living space on the city map, the optimization model in both variants must contain constraints for a minimum and maximum number of inhabitants on the map, since this requirement must be met in any case during city planning. Due to the negative economic effects of the building development in terms of UHI intensity, the map must not contain more buildings than necessary but at the same time must meet the demand for residential space without bottlenecks.

The map of the urban area is loaded into the optimization model, where every pixel of the map, which should be optimized has specific x and y coordinates to identify it within the database. A constraint will subsequently ensure that each pixel or cell is either a built-up-area or non-built-up-area and therefore must be populated exactly once. These three constraints containing the residential space and the allocation of every pixel once are identical for both model variants. The fourth constraint is model variant-specific: UHI minimization means that the UHI intensity is defined as the objective function. A constraint to keep the revenue at a minimum level is specified by the input parameters additionally. For the model with revenue maximization, the revenue function is the objective function, while in the restrictions a predefined UHI intensity level must not be exceeded.

The definition of the UHI function is identical for both models, independent of the role as an objective function or a constraint. The only difference, however, is that the UHI function is minimized in the UHI minimizing model version and restricted by a maximum level within the revenue maximizing version. The UHI intensity of the map is derived from a method from Deilami et al. (2016): The regression equation of a cross-sectional geographically weighted regression (GWR) analysis consists of an intercept in addition to β_1 multiplied by the population density plus β_2 multiplied by the porosity. The calculation yields to the UHI intensity of the respective solution in the model. Since the cross-sectional GWR determines locally specific results for the three beta coefficients, these specified values are inserted depending on the district to be optimized.

The population density is defined as the number of inhabitants on the map divided by the total size of the district in km^2. In the case of porosity, the model strictly distinguishes the two states, pervious and impervious surfaces. If a building is placed on a pixel of the map by the model, this pixel is considered to be a built-up-area and, therefore, as impervious surface. The porosity within the UHI function reflects the proportion of the non-built-up area to the total area, as defined by Deilami et al. (2016). The population density and porosity of the map are deciding factors for the computation of the resulting quality. However, it does not matter where the built-up-areas on the map were placed. It does not change the overall quality of the optimized solution if all buildings are placed on one spot or distributed in the corners of the map. Since we pointed out in the morphological analysis that a maximum distance between the buildings must be maintained, we integrated this into the first stage of the model. Therefore, a function regarding the distance between buildings is implemented for each model.

At this point, the consideration arises to maximize the distance via a second objective function in order to ensure the greatest possible distance between the built-up pixels. However, since this is not optimal in the context of optimization models, the distance is integrated as a further constraint with a minimum distance to be maintained and defined as a parameter before optimization in both model variants.

The following sections comprise the concrete implementation of the conceptual ideas for the optimization model into the two formal mathematical decision models for both variants.

Optimization Model for Revenue Maximization

Assumptions and Notations

In this first model, the revenue of the entire map is maximized within the objective function. The revenue is defined within the model framework as the amount of monetary units that the city planners and the government can achieve selling the land in a typical scenario to investors who builds on the acquired building sites. For the revenue maximization, there is an upper limit as soon as all cells of a map are sold and built on. Altogether, the model consists of two sets: On the one hand, there is a set consisting of all cells or pixels $p \in P$ within the map; cell and pixel are used synonymously. To be able to assign each pixel to an exact location, each $p \in P$ has the coordinates KX_p and KY_P. In addition, a set of all possible alternatives $a \in A$, from which the model must select exactly one for each pixel, is introduced. There is furthermore a subset $b \in B$ of A, which contains all building types. The set $a \in A$ contains the buildings as well as the vegetation alternatives. A constraint is required for the lower ($DMin$) and upper limit ($DMax$) regarding the number of inhabitants on the map.

In a feasible solution, each cell $p \in P$ of the map must be populated exactly once with an alternative $a \in A$. The model has the binary decision variable x_{pa}, which takes the value 1 if the alternative a is placed on the cell p. Each alternative a has a sale price of e_a and a number of available residential spaces s_a. Thus, the total sum of all available places s_a on the map can satisfy the overall residential demand between $DMin$ and $DMax$. For the constraint of the UHI intensity compliance, the regression equation of the cross-sectional GWR analysis according to (Deilami et al. 2016) is used. The general equation equals:

$$UHI = \beta_0 + \beta_1 * PopulationDensity + \beta_2 * Porosity \tag{1}$$

The coefficients β_0, β_1 and β_2 correspond to the results of the research by (Deilami et al. 2016) and are to be inserted in accordance with the specific district. In this model version for revenue maximization, an upper limit $UHIMax$ is set for the maximum UHI intensity level that must be met in order to create a feasible solution. For the overall distance, a distance matrix with the respective distances w_{p1p2} is first calculated using the coordinates KX_p and KY_p of each cell $p \in P$. Afterwards, the respective distance w_{p1p2} is multiplied by the two decision variables x_{p1b1} and x_{p2b2} for the pixels $p1$ and $p2$ and summed up over all cells $p \in P$, in order to include only the cells built with buildings (built-up-area) in the distance calculation, since finally the distance between the buildings is considered only. In order to keep the model linear, another decision variable $y_{p1b1p2b2}$ and three additional constraints were introduced, but the logic of the approach remains fully preserved.

Formal Description

Based on the assumptions and notations, the optimization model follows:

$$\max f = \sum_{p \in P} \sum_{a \in A} x_{pa} * e_a \tag{2}$$

Subject to the restrictions:

$$\sum_{p \in P} \sum_{b \in B} x_{pb} * s_b \geq DMin \tag{3}$$

$$\sum_{p \in P} \sum_{b \in B} x_{pb} * s_b \leq DMax \tag{4}$$

$$\sum_{a \in A} x_{pa} \leq 1 \qquad \forall\, p \in P \tag{5}$$

$$\beta_0 + \beta_1 * \left(\frac{\sum_{p \in P} \sum_{a \in A} x_{pa} * s_a}{Areasqkm} \right) + \beta_2 * \left(\left(1 - \frac{\sum_{p \in P} \sum_{b \in B} x_{pb}}{|P|} \right) * 100 \right) \leq UHIMax \tag{6}$$

$$\sum_{p1 \in P} \sum_{b1 \in B} \sum_{p2 \in P} \sum_{b2 \in B} w_{p1p2} * y_{p1b1\,p2b2} \geq DistMin \tag{7}$$

$$y_{p1b1p2b2} \leq x_{p1b1} \qquad \forall\, p1 \in P, b1 \in B, p2 \in P, b2 \in B \tag{8}$$

$$y_{p1b1p2b2} \leq x_{p2b2} \qquad \forall\, p1 \in P, b1 \in B, p2 \in P, b2 \in B \tag{9}$$

$$y_{p1b1p2b2} \geq x_{p1b1} + x_{p2b2} - 1 \qquad \forall\, p1 \in P, b1 \in B, p2 \in P, b2 \in B \tag{10}$$

Verbal Description

For the calculation of the total revenue within the first objective function (2), the sum over all cells $p \in P$ and alternatives $a \in A$ of the decision variable x_{pa} multiplied by the expenses e_a is calculated. The first two constraints (3) and (4) concern the demand of living space for the whole map. A feasible solution must put at least as much living space on the map to fulfill *DMin* but not exceed *DMax*. The second condition (4) is important because otherwise, the whole space of the map would be built up due to the highest possible revenue level (excluding the restriction of the maximum UHI intensity). For the computation of the total residential space, the sum of all $p \in P$ and all $a \in A$ is formed, and the decision variable x_{pa} is multiplied by the respective living space supply s_a of the building alternative $b \in B$. The constraint (5) ensures that each cell $p \in P$ is assigned an alternative $a \in A$ exactly once. For this, it applies that for each $p \in P$ the sum over all $a \in A$ for all decision variables x_{pa} must take exactly the value 1. Since then, for a specific alternative $a \in A$ the value of x_{pa} is 1 and consequently for all further alternatives from A the value of x_{pa} has to be 0.

In this model version, the UHI effect is integrated into the model within the constraint (6). The inequality ensures that a certain value for the UHI intensity *UHIMax* is not exceeded within a feasible solution. For the calculation of the UHI intensity, the population density and the porosity of the map are needed. The population density is defined as the number of residents per living area in km^2. Since the total number of inhabitants of the map has already been determined within the objective function (2) of this model variant, this formulation can be adopted for the population density counter. The area of the whole map in km^2 is defined by the corresponding input parameter. The porosity is defined within the model environment as the share of the non-built-up area out of the total area. For the calculation, the number of cultivated cells is determined first and then divided by the total number of all cells. The resulting built-up ratio is subtracted from 1 to obtain the non-built-up ratio. This non-built-up ratio is then multiplied by 100, according to (Deilami et al. 2016). The population density and the porosity are then inserted into the regression equation of the GWR analysis (1) to determine the UHI intensity of the solution. As mentioned before, this value of the UHI intensity must not exceed *UHIMax* within the optimization process.

The function (7) determines the distance between built-up cells. For this, the sum of all cells $p1, p2 \in P$ and buildings $b1, b2 \in B$ is calculated by multiplying the distance w_{p1p2} between the cells $p1 \in P$ and $p2 \in P$ with the decision variable $y_{p1b1p2b2}$, which only takes the value 1 if a building $b1, b2 \in B$ is placed on both cells within the optimal solution. This calculated value for the distance must not fall below the parameter *DistMin* during optimization to ensure a corresponding distance within the solution. The final constraints (8) to (10) are necessary for the linearization of the model and are part of the total distance calculation in constraint (7).

Optimization Model for UHI Minimization

Assumptions and Notations

The second model variant minimizes the UHI intensity. Hereby, the UHI effect is minimized with respect to the temperature change in degrees Celsius in the objective function while adhering to a limit for the minimum deviation. Since this version differs only slightly in terms of the notation from the first version, this section only highlights the differences between the two versions. The symbols of this model version are the equivalent to those of the previous section, only *UHIMax* is replaced by *RMin* due to the different roles of the UHI as the objective function within this version.

As an objective of this model version, also every cell $p \in P$ has to be populated with one of the alternatives $a \in A$, whereby each p has to be populated with exactly one alternative a. The two constraints for the demand for housing with the two limits *DMin* and *DMax* are also included. The decision variable x_{pa} takes the value 1 again if the alternative a is placed on the cell p. For the calculation of the UHI intensity as an objective function, the regression equation of the analysis by (Deilami et al. 2016) is used.

The objective function with the UHI intensity as the objective function value is therefore defined as follows:

$$UHI = \beta_0 + \beta_1 * PopulationDensity + \beta_2 * Porosity \tag{11}$$

In this equation, the symbols *BN*, *BO* and *BT* represent the coefficients of the GWR according to (Deilami et al. 2016) and have to be chosen location specific. In this model version, it is still assumed that population density corresponds to the sum of the inhabitants per km^2 and that the porosity is defined by the ratio of vegetation as non-built-up area and buildings as built-up area or impervious surface. The calculation of the revenue for the adherence to the minimum limit *RMin* is calculated analogous to the first model version as the sum of all individual revenues of all pixels $p \in P$ sold to investors for the development of the areas. The distance optimization in the sense of meeting the value *DistMin* between the pixels declared as built-up-areas is identically contained in this version in the linearized version.

Formal Description

Based on the assumptions and notations, the optimization model follows:

$$\min f = \beta_0 + \beta_1 * \left(\frac{\sum_{p\in P}\sum_{a\in A} x_{pa} * s_a}{Areasqkm}\right) + \beta_2 * \left(\left(1 - \frac{\sum_{p\in P}\sum_{b\in B} x_{pb}}{|P|}\right) * 100\right) \tag{12}$$

Subject to the restrictions:

$$\sum_{p\in P}\sum_{b\in B} x_{pb} * s_b \geq DMin \tag{13}$$

$$\sum_{p\in P}\sum_{b\in B} x_{pb} * s_b \leq DMax \tag{14}$$

$$\sum_{a\in A} x_{pa} \leq 1 \qquad \forall\, p \in P \tag{15}$$

$$\sum_{p\in P}\sum_{a\in A} x_{pa} * e_a \geq RMin \tag{16}$$

$$\sum_{p1\in P}\sum_{b1\in B}\sum_{p2\in P}\sum_{b2\in B} w_{p1p2} * y_{p1b1\,p2b2} \geq DistMin \tag{17}$$

$$y_{p1b1p2b2} \leq x_{p1b1} \qquad \forall\, p1 \in P, b1 \in B, p2 \in P, b2 \in B \tag{18}$$

$$y_{p1b1p2b2} \leq x_{p2b2} \qquad \forall\, p1 \in P, b1 \in B, p2 \in P, b2 \in B \tag{19}$$

$$y_{p1b1p2b2} \geq x_{p1b1} + x_{p2b2} - 1 \qquad \forall\, p1 \in P, b1 \in B, p2 \in P, b2 \in B \tag{20}$$

Verbal Description

In the objective function (12), the UHI intensity of the entire map is minimized over the sum of all cells $p \in P$. As already mentioned in the model assumptions, the beta coefficients of the regression analysis by (Deilami et al. 2016) are inserted into the corresponding parameters *BN*, *BO* and *BT* according to the location chosen for the optimization. The corresponding calculations regarding the population density and porosity are performed for the respective sums for all cells $p \in P$ and the corresponding alternatives from the sets A and B identical to the description of the first model version corresponding to the revenue maximization.

The restrictions (13) to (15) are also unchanged compared to the previous description and ensure that the minimum and maximum population levels are adhered to as well as the restriction that each cell $p \in P$ is optimized exactly once with regard to the placement of an alternative from the set A. The constraint (16) ensures the minimum revenue limit. Since the UHI intensity for a certain minimum revenue limit is minimized in this model version, the sum of the individual revenues for each p over all $p \in P$ must be greater than or equal to the value of the parameter *RMin*, which has to be defined by the analyst beforehand in order to meet economic interests.

The constraints (18) to (20) together with the distance constraint (17) ensure that the distance between buildings of the optimized solution exceeds the parameter *DistMin*. We conclude that both models have similar results, if the constraints are tightened reasonably. These models are now included in the following section and integrated subsequently into the DSS and the overall framework for the decision support.

Decision Support System

Overall Structure

This section takes up the optimization model in both variations meaning the revenue maximization and the UHI effect minimization objective functions and introduces the DSS as a holistically integrated construct of input, model and output. The decision maker is able to choose between the two model versions in the GUI depending on the individual optimization objective. In addition, the decision maker is allowed to choose between the exact, deterministic solution (which for large use cases provides the exact result with the disadvantage of a longer computing time) and the heuristic optimization. Once the input data from Microsoft Excel has been transferred to the selected model using the corresponding GUI, the subsequent optimization is carried out and the results loaded into R via text files. The data are processed and visualized for the decision maker to provide a quick and intuitive overview of the solution, which is necessary in order to provide full decision support.

The description of the new artifact starts with an explanation of the input methodology. Since the tool gives the city planning stakeholders a quick introduction to the functionality of this solution, a Microsoft Excel-based solution (referred to below as Excel) will be used to maintain the input parameters. The advantages of using Excel are, on the one hand, its widespread as standard software for spreadsheet calculation, which means that decision-makers usually have a well-established knowledge of the software before learning to use the DSS. On the other hand, Excel offers a high flexibility in saving files, which can be saved as .txt or .csv files in addition to Excel's own .xlsx format. This level of flexibility offers the possibility for the exchange of subsequent steps within the DSS.

By using the inputs, a distinction must be made between the implementation in GAMS (General Algebraic Modeling System) and LocalSolver. By using the LocalSolver implementation of the model, the input file in Excel is saved in .txt format and all parameters are read in. Regarding the implementation in GAMS, a hybrid solution is chosen from an .xlsx file and the GAMS own .include file. In the GAMS variant, all parameters having an index are imported using the external Excel file. This externalization has the reason that in GAMS the .xlsx files must first be converted into .gdx formats and therefore the import of parameters using GAMS own .include format offers a faster computing time. When inserting parameters with an index, however, entering the data in Excel is more comfortable for the analyst, as Excel offers the possibility to logically continue data series by simply dragging them down and thus saving time, especially in the process of implementing coordinates of a large number of cells. By creating parameters within the .include file, this possibility does not exist and each number has to be entered individually, which means a lot of work for highly scaled use cases with a high number of cells.

Since the optimization problems are mixed integer problems (MIP), the CPLEX solver from IBM can be selected as the solution solver. We implemented the optimization models in GAMS using version 28.2.0. In the implementation, both model versions are similar, only the functions of the UHI calculation and the revenue each act once as the objective function and once as a restriction. First, the corresponding sets, parameters, and variables are defined in GAMS. The functions are identical in terms of the calculation of the revenue and the UHI intensity for both model variants with the exception that there is *UHIMax* for the revenue maximization and *RMin* regarding the minimum revenue for the UHI minimization. The terminology for the parameters and the variables is based on the formal decision models.

The objective function defines the goal to be optimized. The constraints must be respected in order to achieve a feasible solution. Finally, the result calculation equations do not influence the final solution but are used to determine and output key values resulting from the solution, such as population density or porosity. To integrate the input from Microsoft Excel, GAMS offers the option of converting Microsoft Excel .xlsx files into .gdx format, which can be read by GAMS and included in the optimization as input parameters subsequently.

Graphical User Interface (GUI)

In general, an attractive GUI design is important as it represents the direct contact between tool and analyst. The GUI must be designed in a way the analyst enjoys working with the overall tool. The mock-up in terms of representing the DSS GUI using a laptop can be found in Figure 1.

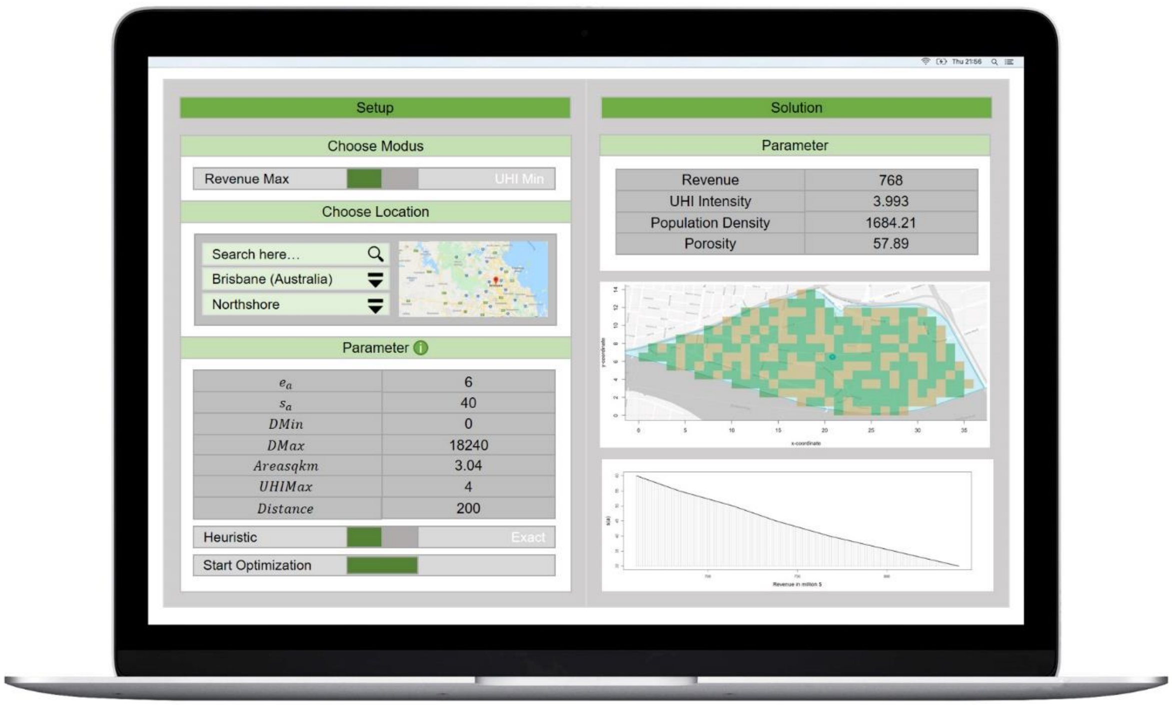

Figure 1. DSS GUI Mock-up on a Laptop

The complexity of the models is reduced by creating a tool and a GUI, which allows an intuitive introduction and finally represents only the most important information for the decision maker. Regarding the general concept, the tool is web-based and therefore executable on any device. Operating the DSS on a server has the advantage that the analyst always includes the latest version and updates. For example, new regression values and locations for the tool can be integrated for the analyst without actively updating the software.

The presentation does not claim to be complete and, like the entire DSS, is in an early stage of development. It is therefore a first concept for the presentation of a GUI. The DSS GUI is divided into two columns. The setup for the optimization is done within the left column, while the results of the optimization are displayed in the right column. As the tool should run on almost all devices without a local installation due to the web-based architecture and the GUI, this concept is ideal for splitting for a tablet display. A first impression using a tablet is provided by Figure 2, where the analyst can switch between the setup and the solution GUI by touch input.

Figure 2. DSS GUI Mock-up on a Tablet

In the first step of the optimization, the analyst must select the mode, in which the two variants of the optimization model can be chosen. In Figure 2, the variant for maximizing revenues is selected. Since the optimization of the planning overview is site- specific, the analyst must select the location within the next step. This is required to insert the corresponding GWR analysis coefficients into the optimization model of the DSS. The location search can be carried out using various criteria such as name or postcode of the corresponding location.

To complete the configuration of the setup, the third step is to select the parameters for the optimization. The optimization process is solved almost in real time using the heuristic approach. The real-time solution means that the decision maker only must wait a few seconds for the optimized solution to be displayed. Therefore, it is possible to vary the inputs within the DSS on the left side and to receive a direct feedback on the changes within the solution on the right side in terms of the new optimized solutions. If the exact optimization with GAMS is selected within the DSS, real-time optimization can no longer be guaranteed. However, in this variant, the quality of the solution can be better than the quality of the heuristic. If the parameters are fixed by the analyst, a more time-consuming exact optimization can be performed.

On the left side of the DSS GUI, there are the solution outputs of the optimization. Four central parameters of the optimization are shown to the analyst in order to provide an overview about the most important key values. In the selected model version for revenue maximization in Figure 2, the revenue represents the objective function value and is displayed to the decision maker as well as the resulting values for UHI intensity, population density and porosity.

The dashboard is completed by two visual representations of the optimized solution. In the first representation, a map of the selected location is displayed with the colored pixels of the optimization. Here, the analyst gets a direct visual overview of the solution by displaying built-up areas and areas populated with vegetation. The presentation can give the decision maker a first feeling of how much the corresponding area is built if the optimal solution is implemented. Since the analyst can vary the number per inhabitants of built-up area of the alternative $a \in A$ by the parameter s_a, a direct feedback can be received by the second visualization in the context of a sensitivity analysis of the graph.

Discussion and Conclusions

This paper deals with the research question of how city planners and policymakers can maximize revenue in the future while limiting the UHI intensity. To this end, we have developed a DSS with an optimization model at its core, which optimizes the corresponding urban areas with respect to the highest possible revenue while maintaining an optimal building/vegetation balance. The tool provides appropriate decision support for the planning process before the sale, as existing tools such as ENVI-met can simulate the microclimatic conditions of the environment in detail, but do not link these findings to economic interests. The objective of the tool must, therefore, show city planners, based on quantitative values, that it is necessary to integrate appropriate countermeasures of the UHI effect, such as the integration of vegetation zones in the relevant districts.

We developed an optimization model in two variants, which on the one hand maximizes the revenue while keeping a UHI maximum limit and on the other hand minimizes the UHI intensity while keeping a minimum limit for the revenue. The creation of both variants is due to the fact that the objectives of the city planners can be individually different. In order to map the financial consequences of an increase in UHI intensity within a discounted cash flow model in the future, further research projects based on this paper are required. An optimization model which offers a comprehensive discounted cash flow calculation in the future, including a variety of economic factors such as site-specific land prices, electricity costs for energy demand and air conditioning, as well as a variety of possible alternatives for building and vegetation types, and which can also perform microclimatic simulations with a level of detail similar to ENVI-met, would probably be the ideal solution for filling the identified research gap and answering the research question posed. Therefore, this can only be answered partially and with a first concept of the early model versions.

In conclusion, there is a high demand for research creating a holistic solution of economic and ecological factors for the overall problem of an increasing UHI intensity. There is a need to support a DSS for cost-benefit analyses of actions city planners might take to mitigate the UHI effect to create the more sustainable cities.

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