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Research article

How to account for spatial trade-offs in planning for urban climate adaptation? Optimizing green and grey infrastructures

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ABSTRACT

Urban Nature-Based Solutions have emerged as sound strategies for urban climate change adaptation, but they lack effective decision-support tools. This paper proposes a decision-support framework that relies on Multi-Objective Optimization (MOO), the consideration of actual space availability, the consideration of the simultaneous objectives of climate change adaptation and water management, the integration of demand for co-benefits, and the participatory exploration of trade-offs for decision-makers. The MOO is applied to the case study of the French city of Bordeaux, to identify the optimal location of Groundwater Recharge Infrastructures (GRI) that include Nature-Based Solutions. It provides decision-makers with spatially explicit solutions for developing GRI, with the objectives of maximizing groundwater recharge, maximizing urban cooling, while minimizing opportunity costs, in the context of urban climate change adaptation. Results indicate an array of solutions between two polar strategies: large scale specialized grey solutions in most effective recharge areas, or diffused Nature-Based Solutions to satisfy citizen demand for multiple benefits. The participatory trade-off analysis proposed in this paper is a novel way to co-design spatial climate change adaptation strategies in urban contexts.

1. Introduction

In the face of climate change and rapid urban growth, cities encounter substantial challenges, e.g. a rise in the frequency and intensity of extreme weather events, the emergence of heat island effects and the contamination of air and water resources (Dodman et al., 2022). Nature-Based Solutions (NBS) are increasingly considered as cost-effective methods to address these urban challenges (Nesshöver et al., 2017), by providing Ecosystem Services (ES), simultaneously providing human well-being and biodiversity benefits (IUCN, 2016).

Urban decision-makers require spatially explicit decision-support systems for planning the development of NBS (Frantzeskaki, 2019). Firstly, they need to account for a wide range of objectives with limited resources and scarce available space for developing public NBS in dense cities (Bush and Doyon, 2019). Climate change adaptation competes

with other potential urban planning objectives, e.g. housing and commercial development, infrastructures, etc. The urban planning decision problem is therefore more complex than just implementing NBS where the conditions are the best to manage one problem (stormwater management for example). Rather, it is a complex spatial problem: how to allocate optimally the available areas and public budgets in order to provide the best possible outcomes?

Secondly, traditional decision-support methods such as Cost-Benefit Analysis (CBA) (Bockarjova et al., 2020; Estrada et al., 2017; Fraga et al., 2021; Johnson and Geisendorf, 2019; Naidoo and Ricketts, 2006; Olanjoye et al., 2021) and Multi-Criteria Decision Analysis (MCDA) (Di Matteo et al., 2019; Langemeyer et al., 2018; Liquete et al., 2016; Martínez-Sastre et al., 2017) struggle with complex spatial problems. They often fail to address multiple, conflicting objectives simultaneously and the potential trade-offs inherent in different scenarios (Langemeyer

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et al., 2016). They also do not handle spatial considerations: in a complex spatial problem where there is an almost infinite number of potential policy scenarios,¹ not all can be soundly represented, analyzed and compared with CBA and MCDA. In consequence, optimal scenarios may not be identified (Seppelt et al., 2013; Turkelboom et al., 2018).

Thirdly, selecting the best available locations for climate change adaptation projects is a complex spatial problem that requires the prior – i.e. *ex-ante* - evaluation of costs and benefits (Tardieu, 2017). Thirdly, a central debate in the context of urban flood management is whether infrastructure development should rely on conventional centralized grey infrastructures or “decentralized” small-scale NBS (D’ambrosio et al., 2021; D. Zhang et al., 2017a), with widely varying outcomes in terms of the distribution of blue and green nature in cities, and on the spatial distribution of Ecosystem Services (Alves et al., 2019; Macháč et al., 2022; Nghiem et al., 2021).

Multi-objective Optimization (MOO) in contrast, is an approach that aims at finding solutions that optimize simultaneously more than one objective function (Deb, 2014). MOO allows decision-makers to explore trade-offs among these objectives and then make informed choices (Emmerich and Deutz, 2018). It relies on identifying a range of optimal solutions known as the Pareto front, which represents the trade-offs between objectives, which makes it a sound method for urban planning and other spatial problems (Jankowski et al., 2014). This paper consequently relies on this method.

MOO has been applied in various NBS optimal location problems (Alves et al., 2020; Bekele and Nicklow, 2005; Dwivedula et al., 2021; Neema et al., 2013; Yoon et al., 2019; Zhang and Huang, 2015; Zhang et al., 2017c). However, MOO is not a widely adopted method in urban planning and NBS decision-making processes. Current applications of MOO may fall short of providing reliable decision-support for three reasons: they do not consider demand for ES, provide few tools to analyze Pareto fronts, and do not analyze the availability of land for implementing NBS.

First, existing MOO applications rely only on modeling the impact of their solutions on the supply of ES, through biophysical indicators, without taking into account the demand for ES. Taking into account only the heterogeneity of supply as a proxy to estimate the spatial distribution of potential NBS benefits may indeed lead to suboptimal location choices (González-García et al., 2020). Population density, which is the most basic indicator of ES demand may for example follow a spatial distribution that is not coherent with biophysical indicators of ES supply. In addition, demand may vary based on the heterogeneity of NBS perceptions, including the potential perception of negative effects associated with NBS (Gould and Lewis, 2016; Laurent, 2011; Lyytimäki and Sipilä, 2009).

Secondly, current MOO applications do not reach the identification of actionable solutions for decision-makers out of the exploration of the Pareto front. MOO studies often stop at revealing the Pareto front (Cao et al., 2011; Dwivedula et al., 2021; Elliot et al., 2019; Yoon et al., 2019; Zhang and Huang, 2015), assuming that stakeholders can independently choose their preferred individual solution within the set. With this assumption, MOO remains a fairly top-down approach with low stakeholder involvement (Girard et al., 2015), and does not necessarily provide tangible help in the decision-making process.

Third, most MOO studies dealing with land use planning and NBS decision-support have neglected the analysis of actual land availability for NBS projects, resulting in optimization and spatial recommendations that are not grounded in practical opportunities. Some works have approached the location optimization of green areas and NBS by first analyzing land availability, though at a small (district) scale (Uribe-Aguado et al., 2022; Wan et al., 2022). This approach has not yet been used at a city-wide scale, for resolving large urban planning

challenges.

This paper presents an innovative MOO approach to address the aforementioned shortcomings in a real decision problem case study. The goal of this study is to provide a proof-of-concept novel approach to decision-support, overcoming the limitations of CBA and MCDA outlined above. The innovations of the developed approach are the following: 1) it relies on an inventory of actual available sites at the scale of a large city, 2) the demand for ES is accounted for; 3) it features a novel participative approach for the exploration of the results of the MOO.

Section 2 exposes the study area and its decision problem. Section 3 presents the MOO approach. The main results are exposed in Section 4, and Section 5 provides discussion and concluding remarks.

2. Study area

This study is applied to the Bordeaux metropolitan area (57,000 ha, 814,000 inhabitants), in France. The municipality faces the main issue of managing sustainably its water supply in the face of climate change and demographic growth. These two drivers may increase the pressure on water resources, which are mainly deep confined aquifers disconnected from the shallow aquifers. In its strategy of water resource management, the local government is planning the development of Groundwater Recharge Infrastructures (GRI) based on infiltration systems - including both Nature-Based Groundwater Recharge Infrastructures (NBGRI) and grey Conventional Groundwater Recharge Infrastructures (CGRI) - at a large scale. These GRI would recharge shallow aquifers with rainwater, thus constituting water stocks that may be used for non-drinkable uses (urban parks and gardens irrigation, street cleaning, industrial uses, etc.), and that would support environmental flows in streams upstream from the dense urban area and the main river Garonne.

The objective of this strategy is to substitute water uses that currently rely on drinking water supply sourced from deep aquifers, even though they do not explicitly require such high-quality water, with water sourced from recharged shallow aquifers. This policy represents a significant shift in the way stormwater is managed, as the city is transitioning from the conventional approach of managing rainwater centrally, which involves collecting and redirecting it away from the city, to embracing decentralized rainwater management solutions. These solutions, such as NBS, rely on the restoration of hydrological cycles and the infiltration of rainwater where it falls.

Additionally, the local government is facing the issue of adapting the city to climate change, mainly by tackling heat island effects, as the average number of days of heat waves in the region may rise from 8.4 per year up to 20.7 by 2050, based on the RCP 4.5 emission scenario (Artelia, 2015). The local government is considering urban greening as a means of improving urban cooling (Livesley et al., 2016) as well as providing other co-benefits. For this reason, NBGRI, which may include several vegetation layers (tree, shrub and herb layer), are considered along CGRI, as a means to achieve simultaneous objectives of groundwater recharge and urban cooling.

Available budgets and space available to develop these solutions are limited. Indeed (public squares, parking lots, school yards ...) in a highly urbanized context² may also be mobilized for other urban plans. Space for developing solutions is constrained since the municipality also aims at not converting more natural and agricultural land use around the city into urban areas (Fig. 1). The pressure on land use is therefore made higher.

The MOO framework is designed to identify optimal ways to allocate land and public budgets within the Bordeaux Metropolitan Area to

¹ With only 100 possible locations, the total amount of scenarios to evaluate is more than 10^{30} .

² In 2018, 49.7% of the land is urbanized, while 21.5% is covered by natural areas, 20.9% covered by agriculture and 8% with humid ecosystems (EEA, 2020).

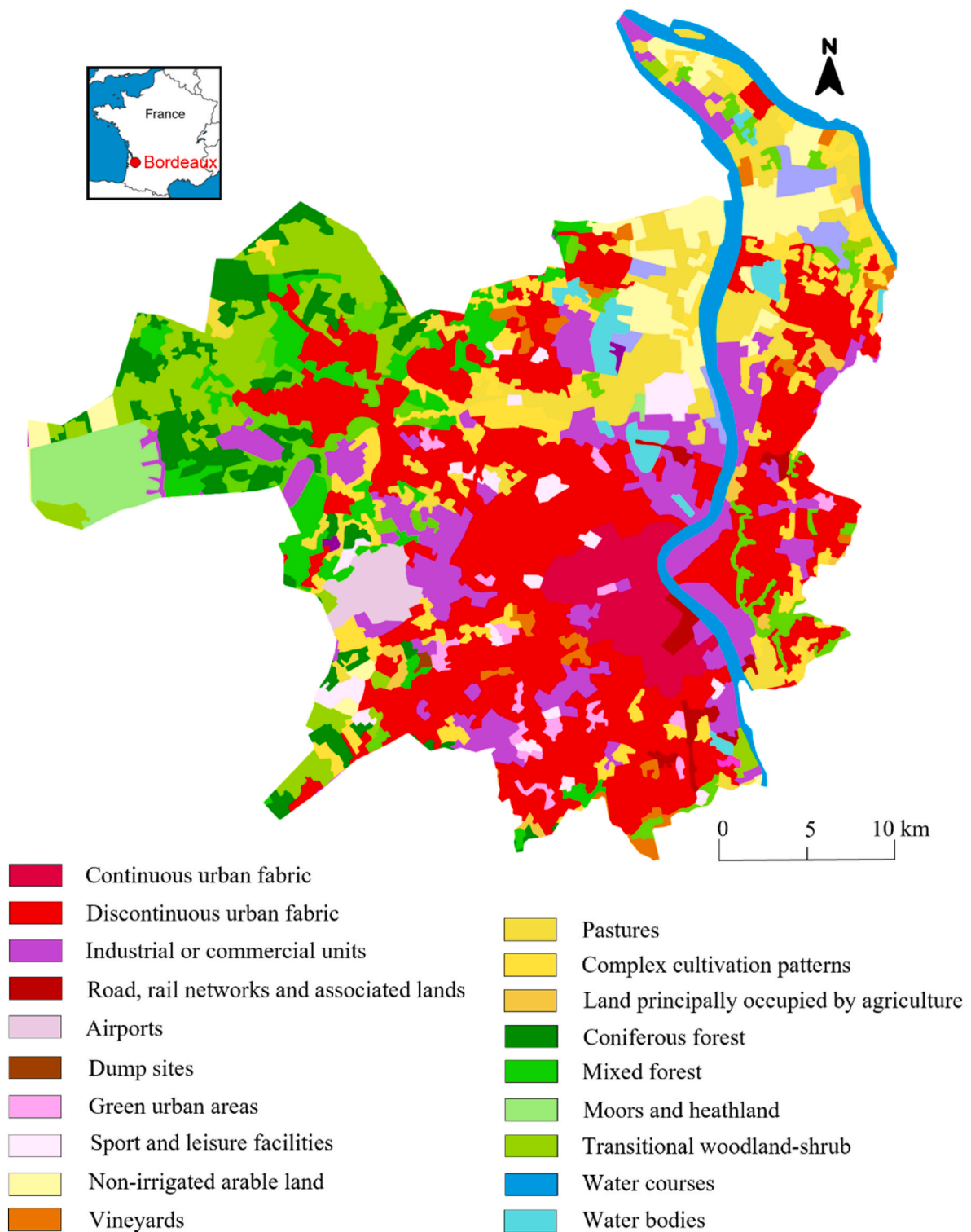


Fig. 1. The Bordeaux metropolitan area and land use in 2020 (Data sources: EEA, 2020).

maximize groundwater recharge and mitigate urban heat islands. It also helps determine which types of infrastructure - whether CGRI or NBGRI - should be developed in each area to achieve these environmental objectives effectively.

3. Method

The goal of this MOO is to search for the best combinations of sites to implement GRI. This means reducing the potentially infinite number of

planning scenarios to the subset of best available options. This section presents the overall design of the MOO, the decision variables, the objectives, and the optimization algorithm (Section 3.1). It then details the identification of potential sites for developing GRI (Section 3.2) and the evaluation of objective functions (Section 3.3). The final section (Section 3.4) presents the Pareto front analysis methods.

The development of this MOO involved a participatory approach that included multiple sessions with key stakeholders at different stages of the process. These stakeholders were representatives of the government

services involved in urban planning and zoning, water management, and urban greening, as well as various public urban developers. A first workshop (October 15, 2020) was conducted to identify the primary optimization objectives and constraints associated with water infiltration and groundwater recharge. An additional brainstorming session (February 11, 2022) was organized with stakeholders to determine suitable locations for the development of GRI. A final interactive session (September 14, 2023) allowed to visualize and discuss the implications of the MOO results.

3.1. The multi-objective optimization design

The main MOO design builds on the design developed by Farina et al. (2024b)

3.1.1. Decision variables

The first question addressed by this MOO is spatial: where to develop groundwater recharge. Potential sites available within the metropolitan area for developing GRI are numerous. Relying on this spatial scale (more than 7000 plots) would therefore be too computationally intensive. The decision variables therefore consist of a list of 271 districts extracted from the French census database (INSEE, 2017). The optimization problem is approached at this spatial scale, rather than focusing on individual plots. This decision was made in consultation with stakeholders, as prioritizing districts aligns with the context of long-term planning and proves more relevant than considering individual plot-level spatial scale. On each of these 271 districts, two types of decision are made.

Firstly, two distinct types of technology can be used: NBGR or CGRI. In order to reduce computational time, the choice of technology type is made at the district level, wherein all plots within the considered district are developed using either one technique or the other. Each district is characterized by the available plots that are located within it (Section 3.2), which are themselves characterized in terms of land cost and groundwater recharge efficacy (Section 3.3).

Secondly, different implementation levels can be considered: the potential plots within the district do not have to be used entirely. GRI may be implemented only on 40% of the available surface, for example. This is a discrete choice between six implementation levels: 0%, 20%, 40%, 60%, 80% or 100% of the potential of plots in any single district can be selected. These percentages only refer to the use of candidate plots within districts, not for the entire city (see effort constraint Section).

Following this design, each solution n to the MOO features I selected districts (implementation level >0), with each individual district i developed with an implementation level r_i and an infrastructure type τ_i . The selection of I districts is composed of two subsets: a subset of J districts implemented with NBS, and $I - J$ districts implemented with grey infrastructures.

3.1.2. Objective functions

The first objective aims at maximizing the effectiveness of groundwater recharge at the scale of the metropolitan area. This objective represents the aim of decisions makers to maximize overall groundwater recharge benefits (R_n). The second objective is urban cooling (C_n) and is approached in this study through the mitigation of heat islands. The third objective of the optimization is the minimization of opportunity costs (O_n). The evaluation functions of each objective are detailed in Section 3.2.

3.1.3. Effort constraint

The MOO features a single "effort" constraint that acts as an upper bound to the total amount of land converted to GRI. The maximum surface area dedicated to recharge infrastructures was set, in agreement with stakeholders to 10% of all available identified plots (Section 3.2), i.e. 369ha in this case. This serves the purpose to limit the searchable

solution space to solutions that are within the implementation capacity of the municipality, while still representing an ambitious maximum level, comparable to other similar plans in French cities.³ Using a space constraint is a simple approach compared to a more traditional cost constraint. It is also an easier indicator to discuss and set for decision-makers rather than costs. There is no difference between the type of solutions with this approach. It therefore does not account for potential implementation cost-effectiveness differences between solutions.

3.1.4. Optimization algorithm

The optimization problem is a combinatorial optimization (Stewart et al., 2004): it looks for the best combinations of districts, infrastructure types and implementation levels. It is solved using the evolutionary algorithm from the DEAP library (Fortin et al., 2012). The algorithm works by creating populations of candidate solutions to the problem, with each solution being the selection of a subset of districts, each developed with one type of infrastructure at a given implementation level. These populations are evaluated, and the best non-dominated solutions are selected, using the NSGA-2 selection algorithm (Deb et al., 2002). The resulting solutions are then kept, as well as used to create new "children" solutions. This generation process is made by two processes: i) by combining two solutions with each other through a cross-over operation, where bits of their components are swapped with each other; and ii) through a mutation operation, where new elements (i.e. new districts) are randomly added or removed from a solution. This process is repeated, simulating natural evolution, until the Pareto front is reached.

The population size is 500 solutions, crossover and mutation probabilities set at 0.7 and 0.3. The algorithm runs until satisfactory solutions are obtained, in this case, after 1000 generations (Fig. 2). This number of generations is decided after trial and error, by incrementing the number of generations across runs, until the Pareto front remains stable. The optimization program is written in Python (v. 3.11)

3.2. Identification of the potential sites

A central input to the MOO is the identification and mapping of real land plots that may be used in the future for the development of GRI. It is the result of a brainstorming workshop (January 11, 2022) with key stakeholders of the Bordeaux Metropolitan area, i.e., urban planners, water distribution and management representatives, urban parks managers, etc. Key land use types suitable for GRI were identified and mapped: parking lots of commercial and industrial areas, schoolyards, open public and private spaces available for urban greening projects (public squares, sidewalks, small parking lots, abandoned lots, etc.). These sites come from the Copernicus Land Use Database (EEA, 2020), the Bordeaux Open GIS Database, as well as local land use inventories realized by the urban greening services of the local government.

This database (Fig. 3), although not exhaustive, provides a good basis for assessing the land potential for implementing GRI and other NBS projects in the area. It was discussed and effectively validated by the local stakeholders as being a good inventory of potential locations to change land use within the urban area.

3.3. Evaluation of the three objectives

3.3.1. Maximization of groundwater recharge

The characterization of groundwater recharge relies on a hydrogeological study conducted in the Bordeaux Metropolitan area, which collected geological and topographical data regarding the capacity of urban soils and aquifers for infiltrating, storing and extracting rainwater for re-use. The most important parameters in determining recharge were

³ The Metropolitan area of Lyon ('Grand Lyon') for instance has initiated a project that aims at deproofing up to 400 ha of artificial soils by 2026.

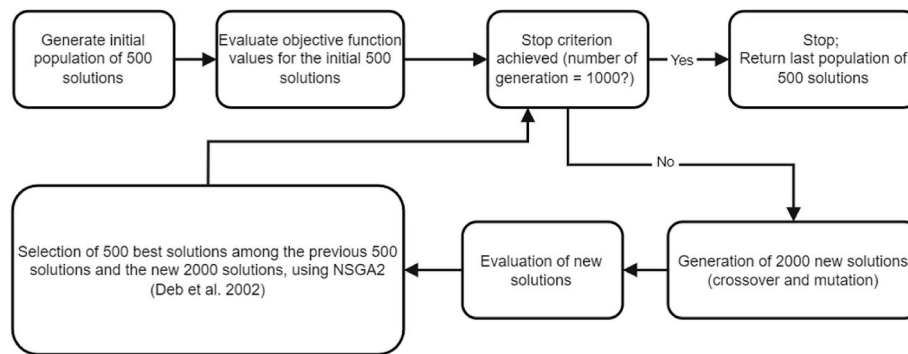


Fig. 2. Main process of the evolutionary algorithm.

identified by stakeholder and expert interviews. They are the soil permeability, the depth of the vadose zone, the aquifer thickness, the terrain slope, the storage coefficient of the aquifer (porosity), and the Network Development and Persistence Index developed by Mardhel et al. (2021).

These parameters were selected in order to consider the capacity to recharge aquifers, as well as to avoid groundwater floodings. In a second round of stakeholder concertation, the most and least favorable range of values for these parameters were identified. In addition, all six parameters were attributed relative weights with a simple multi criteria ranking weighing scheme based on the Analytic Hierarchy Process method. The parameters were aggregated in a final step through a spatial multi-criteria analysis, using the weighting scheme in order to create a final single recharge favorability map. The final result is a recharge favorability map (Fig. 4a). Then each individual site s available for GRI was attributed a value g_s of this score, on a scale of 0–10, according to its location.

The groundwater recharge yield R_n of solution n is calculated as the sum of the groundwater recharge score of all the sites of the I districts that make the solution. The groundwater recharge yield of each district i is itself the sum of the recharge score g_s of each recharge site s within the district, multiplied by the implemented surface of GRI on these sites, which is the product of the plots surface area a_s multiplied by the implementation level r_i of the associated district i (Eq. (1)). This value is unitless. A central assumption is that no distinction is being made in groundwater recharge efficiency between NBGRI and CGRI for infiltration-based systems as regarded. The central factors influencing the groundwater recharge yield are considered to be the soil and sub-surface parameters, following (Bouwer, 2002).

There is in this method a fairly strong assumption: maximizing the amount of surface areas dedicated to recharge projects in areas where recharge effectiveness is the highest is an approximation of the various benefits of such a policy (maximizing water availability, minimizing flood risks, etc.). It does not represent one single tangible benefit but rather a package of potential benefits that depend on recharge effectiveness.

$$R_n = \sum_{i=1}^I \sum_{s \in \text{in } i} g_s^* a_s^* r_i \quad (1)$$

3.3.2. Maximization of urban cooling

The urban cooling effect of NBS is a consequence of increased shading, evapotranspiration and albedo effect (Yu et al., 2020). The urban cooling benefit function is based on a simple representation of the urban cooling effect of NBS, combined with an evaluation of demand for this cooling effect. Two assumptions are made 1) the larger green areas are, the larger the areas of heat mitigation, and 2), this urban cooling benefit (C_n) is composed of two distinct effects: a global and a local benefit. The global part (C_n^G) of the cooling function assumes that implementing NBGRI in the city benefits to the entirety of the city

population, by mitigating the areas of intense heat. The function also features a local benefit (C_n^L) because local urban cooling benefits also directly to the population living close to a NBGRI.

First, the climate cooling effect provided by each plot converted to NBGRI is evaluated. One important assumption is drawn here: this approach does not model the cooling impact of NBGRI in terms of temperature reduction, but instead posit that if a heat island area is within the cooling range of a NBGRI, it will provide sufficient cooling to the extent that the area will no longer be classified as a heat island. Heat islands are defined here as areas where the surface temperature during heat wave episodes is significantly higher than the rest of the metropolitan area (mean temperature + 1 standard deviation) (Rizwan et al., 2008).

The cooling effect occurs on a variable buffer extent surrounding NBGRI (Aram et al., 2019). This cooling effect is modeled by creating buffer polygons on and around implemented NBGRI, in the subset of J districts selected for NBGRI projects, within the I districts selected for recharge projects in solution n . The buffer extent γ_s of each NBGRI is itself a function of the implemented area. This implemented area is the product of the district implementation level r_j in the associated district j and the surface area of the plot a_s , multiplied by a scaling factor σ , set to 10^{-2} (Eq. 2). The buffer extent γ_s then serves as the radius parameter for creating buffer areas around the NBGRI. The scaling factor σ is based on state of the art on the cooling extent of green areas and NBS (Aram et al., 2019). For instance, NBGRI covering total implemented surfaces in our MOO of 0.5 or 2ha would have cooling extents of 50 and 200m respectively. For comparison, estimates by Aram et al. (2019) indicate that a 0.8ha park would have an impact up to 44 m, and a 2.5ha solution, an impact up to 218m.

$$\gamma_s = r_j^* a_s^* \sigma \quad (2)$$

Global C_n^G and local C_n^L cooling benefits generated by this effect for each solution are then calculated. These benefits are an interaction of the cooling effect, with demand for urban cooling. The demand of the residents for urban cooling is based on a discrete choice experiment survey in the Bordeaux area, in which the authors estimated the resident's willingness to pay (WTP) for various benefits of future GRI, and subsequently constituted a map of the population's mean WTP for urban cooling at the district scale (Fig. 4b) (Farina et al., 2024a).

The global cooling benefit function first evaluates the total area of mitigated heat island areas, which is the difference in surface area of heat islands between the solution and the baseline (*i.e.* the current state of heat islands in the Bordeaux Metropolitan area). This global effect benefits to all inhabitants of the metropolis, as they carry out their activities over the metropolis (work, leisure, etc.) and may have altruistic preferences for cooling the city for others. The resulting percentage P_n of mitigated heat island areas is then multiplied by the mean city-wide willingness to pay (WTP) of households for the incremental mitigation of heat island surface areas, equal to 2.946 € per percentage point of eliminated heat island area (Farina et al., 2024a), and the total number

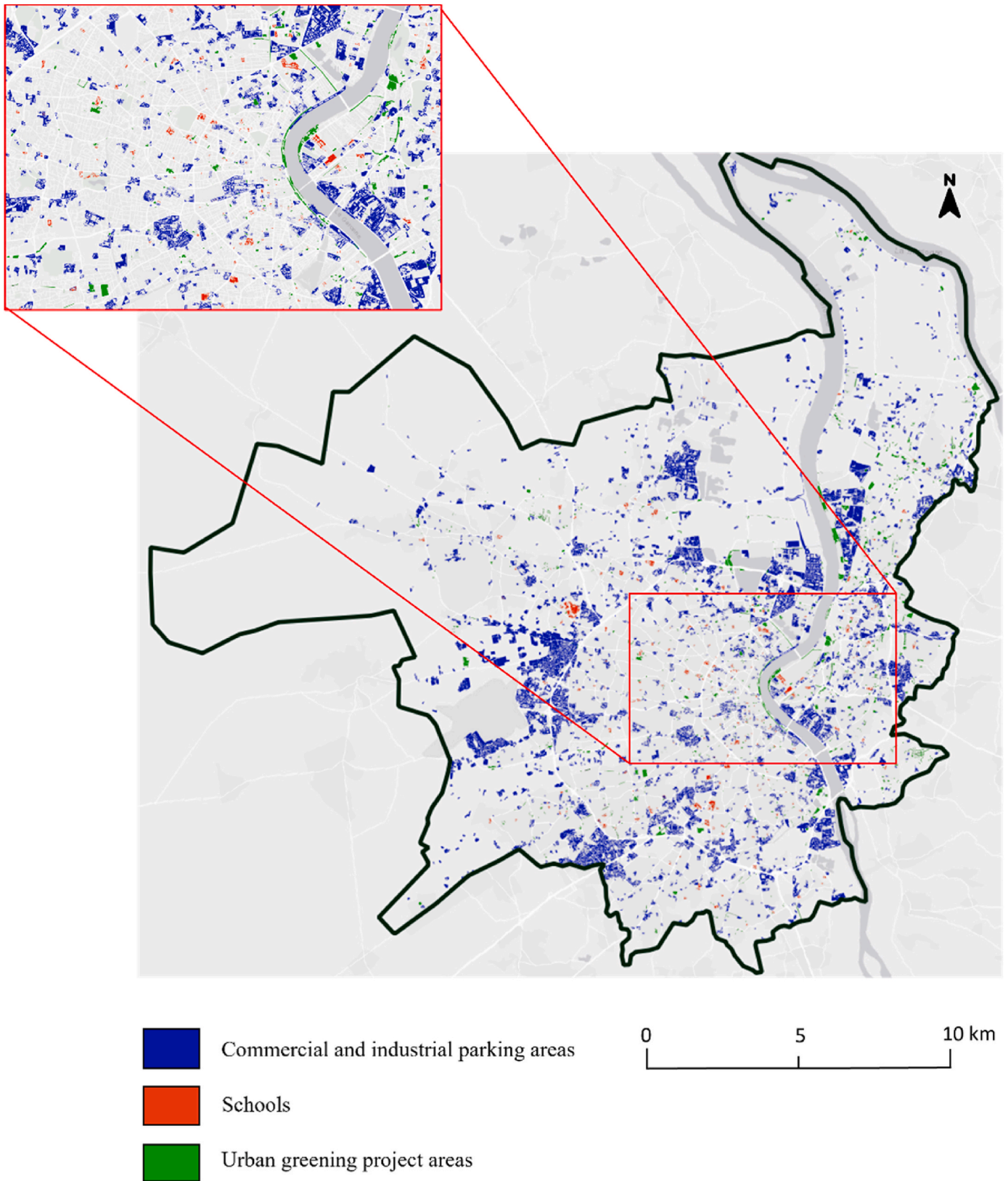


Fig. 3. Available sites for developing infiltration projects in the Bordeaux Metropolitan Area.

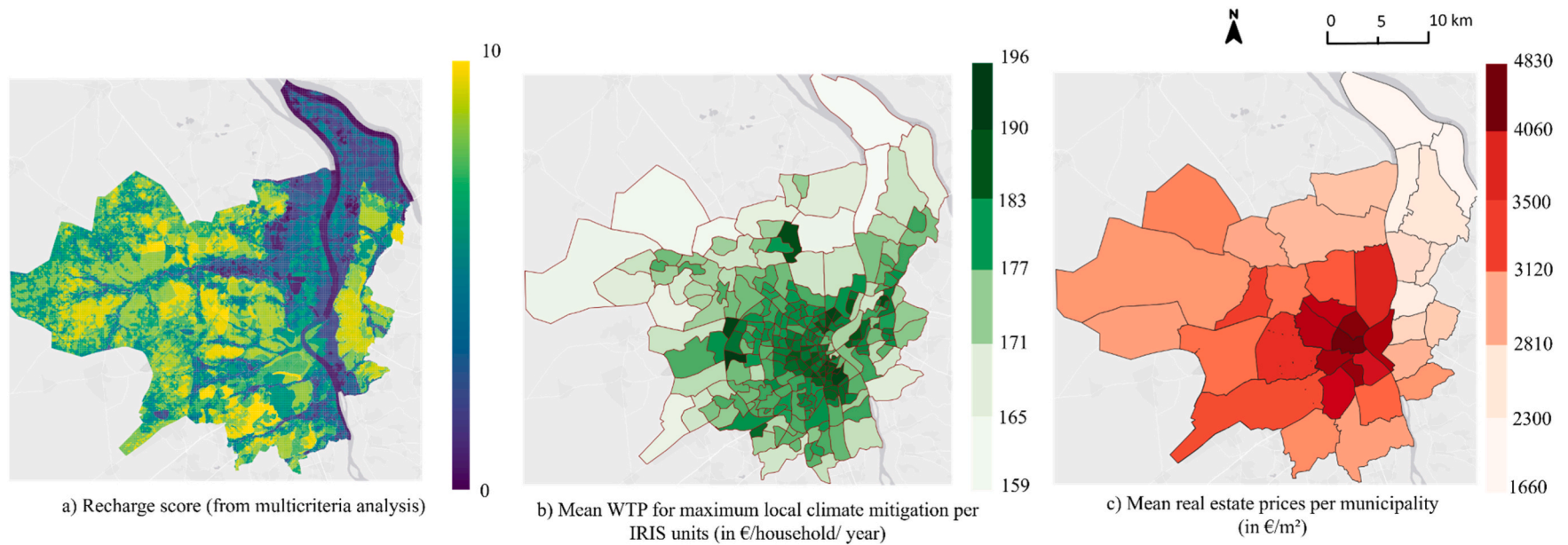


Fig. 4. Indicators used for representing infiltration efficiency, urban cooling and opportunity costs.

a) Multi-criteria score defining groundwater recharge favorability b) The map was made using the relation between mean temperature and WTP estimated in the post-estimation from the choice experiment (Farina et al., in Press). c) Mean land prices are collected from the French notarial database (2018).

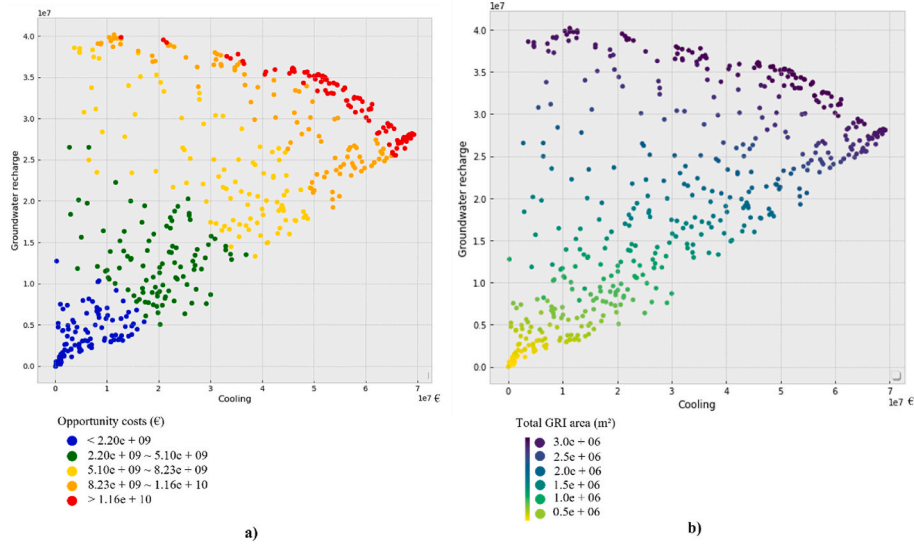


Fig. 5. Optimal solutions of the MOO problem, represented along the infiltration and urban cooling dimensions. In subplot a), the opportunity costs dimension is represented with the five color categories. In subplot b), the total implemented areas of GRI per solution, *i.e.* the “effort” constraint, is depicted with the color scale. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

of households in the BM area (399,989 in 2020) (Eq. (3)).

The local cooling benefit function simply represents that the households h_s living within the cooling buffers of the NBGRI benefit of site s additionally benefit from it, by increased well-being. h_s is estimated by multiplying the buffer surface area by the mean household density of the district. h_s is then multiplied by the variation α_j in mean district-specific household’s WTP for heat island reduction, (Fig. 2b). The result is the total WTP for urban cooling at the district scale. The local cooling benefit C_n^L is then the sum of the benefits of each selected NBGRI district g (Eq. (4)) in euros.

The final resulting cooling function C_n is the linear sum of the global C_n^G and local C_n^L effects (Eq. (5)).

$$C_n^G = P_n * 2.946 * 399\,989 \quad (3)$$

$$C_n^L = \sum_j \sum_{s \in j} h_s * \alpha_j \quad (4)$$

$$C_n = C_n^L + C_n^G \quad (5)$$

3.3.3. Minimization of opportunity costs

Opportunity costs are approached through land prices, thus relying on the assumption that these prices represent the most profitable value of land that would be lost by implementing GRI (Thurston, 2011). This objective acknowledges the challenge faced by decision-makers when implementing policies within the constraints of limited land and resources. Additionally, decision-makers often have multiple policy priorities that compete for land use, such as developing transportation options like bike lanes and public transit systems, as well as creating residential and commercial areas to accommodate population and economic growth. Consequently, policy makers may be motivated to minimize the effects of GRI on land use.

Opportunity costs O_n of solution n is the sum of the land prices of the plots p_s used for implementing recharge infrastructures in euros. These prices from the real estate market in Bordeaux metropolitan area originate from the French notarial database (2020).

An important difference is set between NBGRI and CGRI technolo-

gies: the latter tend to occupy less ground space and are often partially or entirely built underground. As such, they are modeled as having a fraction of the opportunity costs of NBGRI (Haaland & van den Bosch, 2015; Maliva, 2014). This is represented through the τ coefficient, set as 0.5, which is an approximation of the difference in surface size between NBGRI and CGRI for a same recharge effect. A distinction is thereby made between the two subsets of district within the j district of solution n , with J districts selected for NBGRI and $I-J$ districts selected for CGRI infrastructures (Eq. (6)).

$$O_n = \sum_{j=1}^J \sum_{s \in j} a_s * r_j * p_s + \sum_{k=1}^{I-J} \sum_{s \in k} a_s * r_j * p_s * \tau \quad (6)$$

3.4. Pareto front analysis

Two complementary approaches are developed for the analysis of the Pareto front: i) a novel visualization approach, dedicated to trade-offs analysis, as well as ii) a participatory analysis session with key stakeholders.

The trade-offs analysis restricts the focus on a specific area of the Pareto front. It is the section of the front with the highest levels of opportunity costs, *i.e.* the solutions with the highest levels of ambition for the stakeholders. They also represent the largest span of trade-offs between groundwater recharge and urban cooling. These solutions are organized into five quantiles, along the recharge-cooling trade-off dimension. Then, the approach consists in presenting the average implementation levels for each district within the solutions of each quantile, for NBGRI and for CGRI. The result is two series of five city maps, which represent the average intensity of implementation in each district for each trade-off quantile, separately for NBGRI and for CGRI (Fig. 6). Aggregating non-dominated solutions theoretically defeats the purpose of Multi-Objective Optimization. However, this type of representation presents in a manageable way the main trade-offs of the most ambitious solutions.

In the final phase to this study, the results of the optimization were presented to the group of stakeholders (September 14, 2023). This workshop used a two-step method to analyze and explore the results of the MOO, and extract operational recommendations from it. First, the participants were presented the entire methodology, up to the resulting Pareto front and its trade-offs. In a first discussion, the participants were asked to select areas of interest within the Pareto front, alongside the

⁴ Overlaps of buffers are merged in order to avoid double counting of affected population.

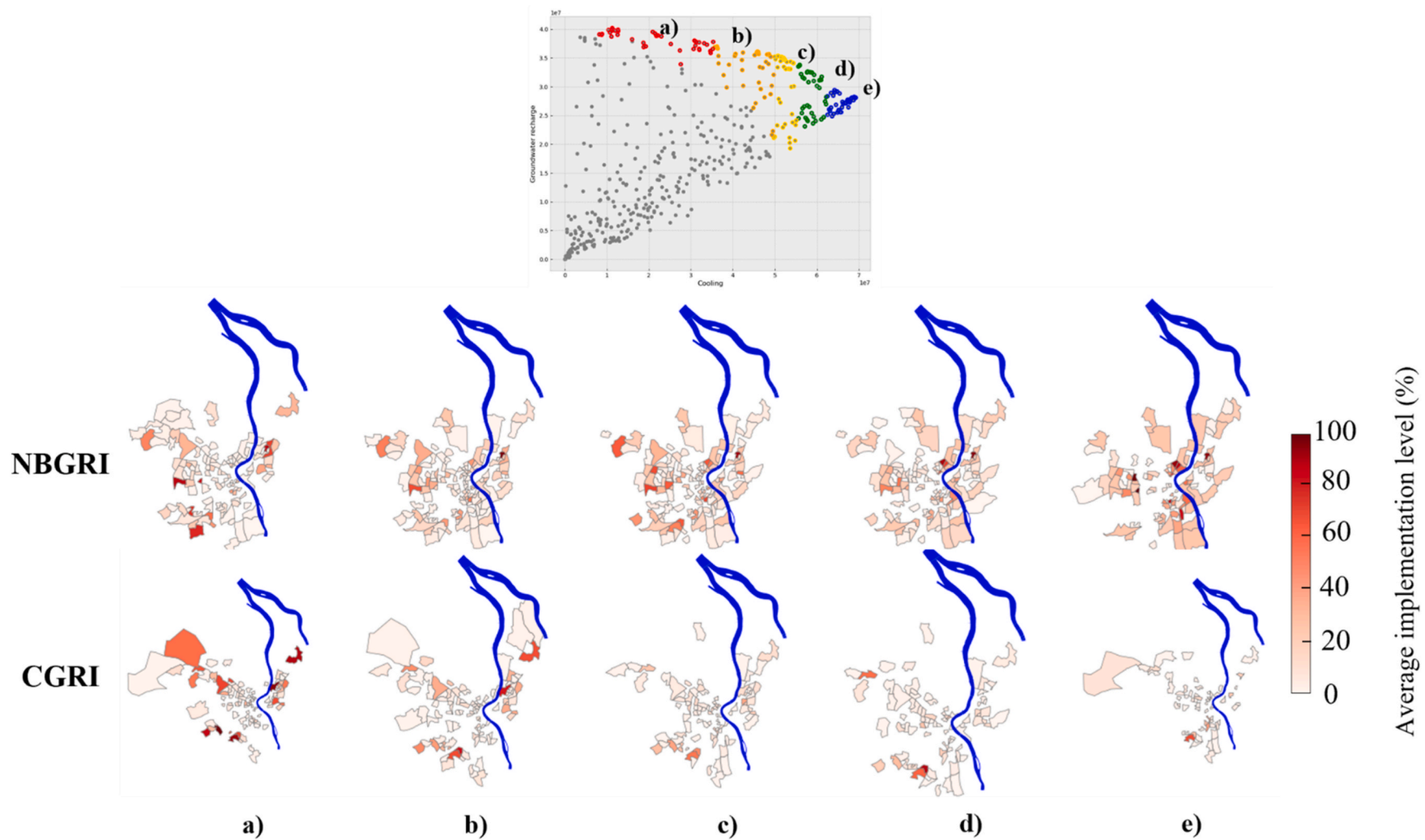


Fig. 6. Trade-off analysis along the high effort front. The red color grading indicates the implementation intensity of each individual district: it is the average implementation levels in each district, across the corresponding subset of solutions. The groups of solutions a,b,c,d, and e originate from the Pareto front analysis method described in Section 3.4. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

justification for their interest on the areas, *i.e.*, what groups of solutions they would like to explore in more details (and spatially). Then, in a second phase, the selected group of solutions - *i.e.* those that created consensus during the first session – were presented to stakeholders using web-maps. These maps present the main spatial patterns of these solutions, the selected districts and sites for developing GRI. The ensuing discussion was oriented towards the analysis of these spatial strategies, their operational implications, and the overall pertinence of the tool.

4. Results and discussion

4.1. Final population of optimal solutions

The final population is made of 500 solutions, each defined by the districts selected for implementing GRI, their implementation levels and technology choices, as well as their objective values in the recharge, opportunity costs and cooling dimensions. This Pareto front is represented in a two-dimensional space, with the opportunity cost dimension

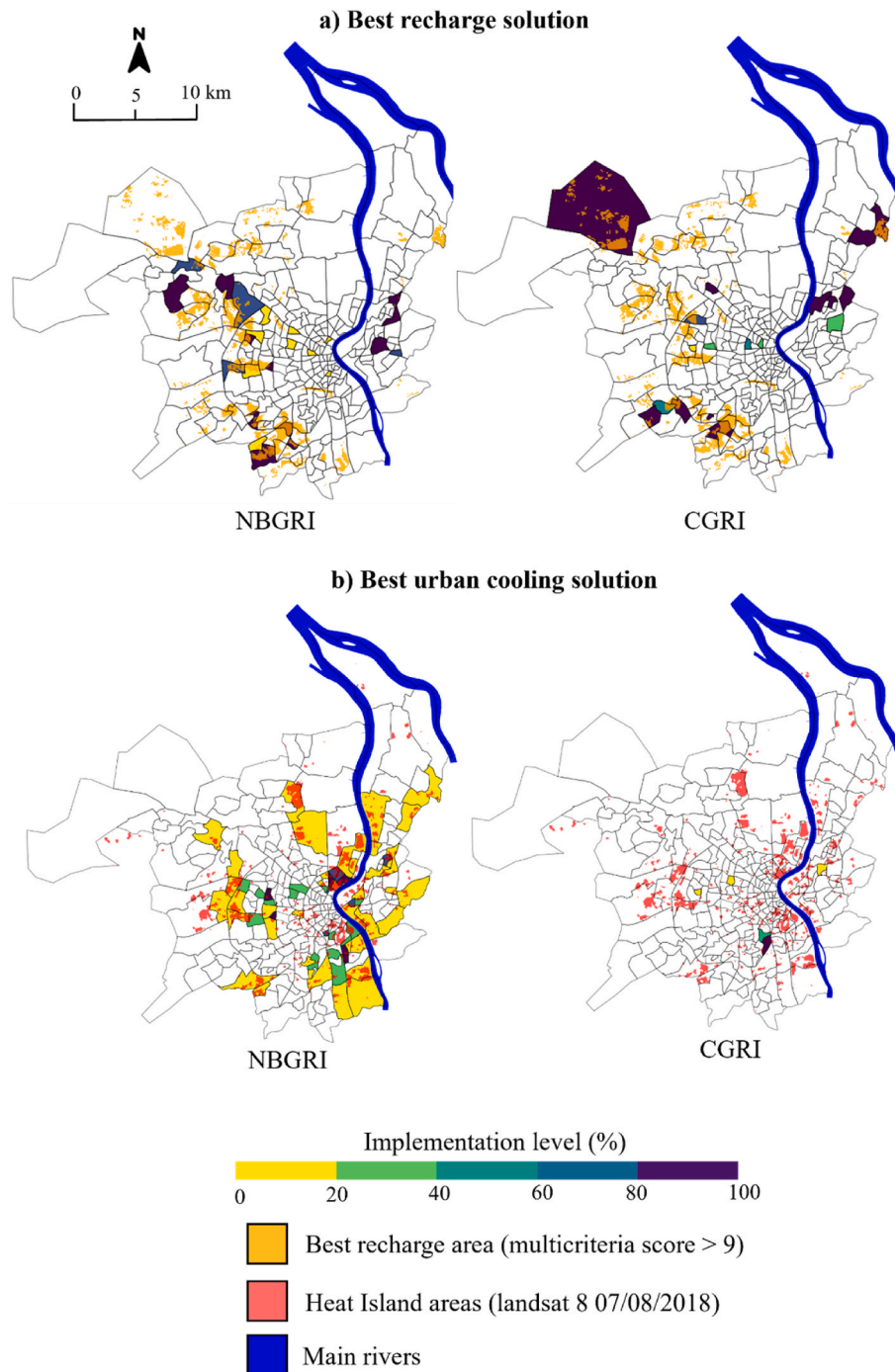


Fig. 7. Best solutions in the recharge and cooling dimensions resulting from the MOO.

The color gradient in the maps represent the implementation level in each selected districts, *i.e.*, what percentage of the available sites are used. The maps on the top present the best recharge solution, with the best areas for recharge, as per the multicriteria analysis (Fig. 2a): this map is filtered to show only the areas with the highest multicriteria scores (above 9 on the 0 to 10 scale). The maps on the bottom present the best recharge solution, with the location of heat island areas during a heat wave episode.

presented in color categories (Fig. 5a).

The front presents several characteristics. First, opportunity costs compete strongly with both other objectives: increasing either recharge or urban cooling requires increasing opportunity costs, and this effect is even stronger for urban cooling. Second, solutions can go to extreme points, which makes them compatible with a single-objective optimization. Third, there is an area of “high effort” on the front, for which the (spatial) effort constraint is saturated. It represents the tradeoffs for the highest attainable impacts. These are all the solutions that are located on the uppermost area of the Pareto front. Fourth, a main aspect of this high-effort area is that the solutions that maximize groundwater recharge (on the top left side of the front) provide relatively low urban cooling, while the solutions that maximize urban cooling (on the top right of the front) also generate a relatively high potential in groundwater recharge, while also belonging to a higher opportunity cost category. Therefore, this maximal urban cooling solution and its surrounding solutions – the area on the top right side – suggests there is a more synergic solution space here, in terms of benefits. In other words, the trade-off between both benefits is less strong in this area of solutions, we can reap both benefits at the same time – though at a higher opportunity cost.

4.2. Trade-off analysis along the high effort front

Fig. 6 presents the maps resulting from the trade-off analysis approach (Section 3.4), focused on the high-effort front. The maps located on the left correspond to the area of the high-effort front where recharge is at its highest and urban cooling the lowest (Fig. 6a). At the other extremity, on the right side, the maps display the area of the front where solutions feature the highest scores in urban cooling (Fig. 6e). The maps between those points (Fig. 6b,c,d) show trade-off solutions that balance more both of these objectives.

First, the solutions on the left side (a), indicate that the “priority” districts – i.e. the most frequently and intensely selected districts either to implement NBGRI or CGRI - are located outside of the city center, in specific areas along the periphery. These districts are selected in almost all solutions of this subset of solutions, with high implementation levels (in deep red). In contrast, the other districts are only occasionally selected. As we move towards the maps on the right side – those that favor more urban cooling - we observe a few changes. In maps (b), (c), (d) and (e), solutions give an increasing importance to NBGRI and use less CGRI, as urban cooling is increasingly favored. Furthermore, the pattern of selected areas shifts gradually. More centric districts are selected, and the implementation of centric areas is gradually rising while peri-urban areas decrease. In group of solutions (e), solutions are mostly constituted of NBGRI and are located either in peri-urban areas with low implementation level, or in centric areas, with a high intensity. CGRI are not totally dismissed, and there are still a few districts that are selected for their implementation, but with a low intensity.

The spatial patterns identified in the extreme groups of solutions ((a) and (e)) can also be identified in the extreme solutions of the Pareto front. Fig. 7 presents the individual solution that maximizes recharge out of the whole front, as well as the solution that maximizes urban cooling. These solutions are similar to the groups presented in Fig. 6a and e. Fig. 7 reveals that the spatial distributions of recharge potential and heat islands are a determining factor of these results. The best recharge solution consists in developing both types of GRI in the areas of the city where recharge potential is the highest, and where there are available plots for developing recharge projects. This solution implies a very dense concentration of GRI in a select few areas. The solution that maximizes the benefits of urban cooling in contrast tends to only require NBGRI, and their location tends to concur with the location of heat island areas.

A reason can also be identified as to why the best urban cooling solution also has a relatively high level of recharge, resulting in an overall synergistic solution. Some districts selected for NBGRI in Fig. 7b (for instance those located in the west side of the city, where there are

noticeable heat island areas), are also selected in the best recharge solution (Fig. 7a). Indeed, heat islands can be located where recharge potential is high. In this context, maximizing urban cooling using NBGRI leads to spatial choices that are also optimal for recharge.

4.3. Participatory analysis of the Pareto front

The final phase of this study consisted in the participatory analysis of the Pareto front.

The first step of it revealed that stakeholders gave particular interest to the solutions located on the high effort front, at the highest level of opportunity costs, at a middle point between urban cooling and recharge. The rationale behind this selection was to pinpoint the most ambitious solutions, considering these solutions as long-term goals, and opt for those that struck a balance between both benefits. The stakeholders subsequently validated the spatial patterns emerging from this area of the Pareto front, noting that they partly matched with their preliminary greening strategies.

In the second step, these solutions were presented spatially to stakeholders with a web-map. The presented map (Fig. 8) is an aggregation of a small subset comprising ten solutions located in the selected area of the front, which typify the prevailing trend within these solutions. This map includes only the districts that are consistently selected across all solutions in the area of interest for stakeholders, effectively designating them as priority districts. They are therefore akin to priority districts. Given stakeholders' expertise and familiarity with the Bordeaux Metropolitan Area and its ongoing adaptation projects, a discussion was conducted to compare the spatial patterns from the web maps with their local knowledge. This facilitated an examination of the feasibility of the proposed spatial strategy, including identifying areas where the MOO recommendations either conflicted with existing projects or demonstrated potential synergies.

The MOO informs on the spatial choices for the implementation of GRI, and the resulting spatial trade-offs. Giving priority to either the aquifer recharge or the urban cooling benefits translates into different spatial and technical choices. In essence, solutions with an emphasis on recharge appear rather as “specialized” solutions, with a relatively small number of NBGRI, and with mostly CGRI implemented in the few areas that feature the best possible physical parameters for infiltrating and storing rainwater, with at the same time low opportunity costs. These solutions therefore tend to concentrate GRI in peri-urban areas, with a high implementation level. Implementing such strategies potentially offers high economies of scale, and a high cost-effectiveness ratio regarding recharge. This spatial pattern does not come as a stark contrast to existing practices - creating large mono-functional infrastructures outside of urban areas. This result also echoes recent studies identifying that centralized large infrastructures may often prove a better option in terms of water peak flow reduction than decentralized small rainwater management infrastructures (Meierdiercks and McCloskey, 2022).

On the other side of the spectrum, solutions with a higher emphasis on the urban cooling objective have distinct designs. They feature mostly NBGRI, more widely scattered near heat islands and not necessarily in the most central area of the city. This contrasts with the theoretical findings obtained by Farina et al. (2024b), which suggested implementing NBGRI mostly in densely populated city centers. However, this previous study did not specifically address the location of heat island areas and solely relied on population as a proxy for demand, leading to the observed disparity. This application to the Bordeaux area demonstrates the importance of a finer representation of the spatial demand for urban cooling. Some CGRI are also implemented in most of these cooling-focused solutions, mostly in the periphery of the center and in peri-urban areas, providing some high recharge yield at a low opportunity cost and with very limited cooling benefits.

The pattern resulting from our MOO also comes as a contrast with current global greening policies, which are mostly aimed at either

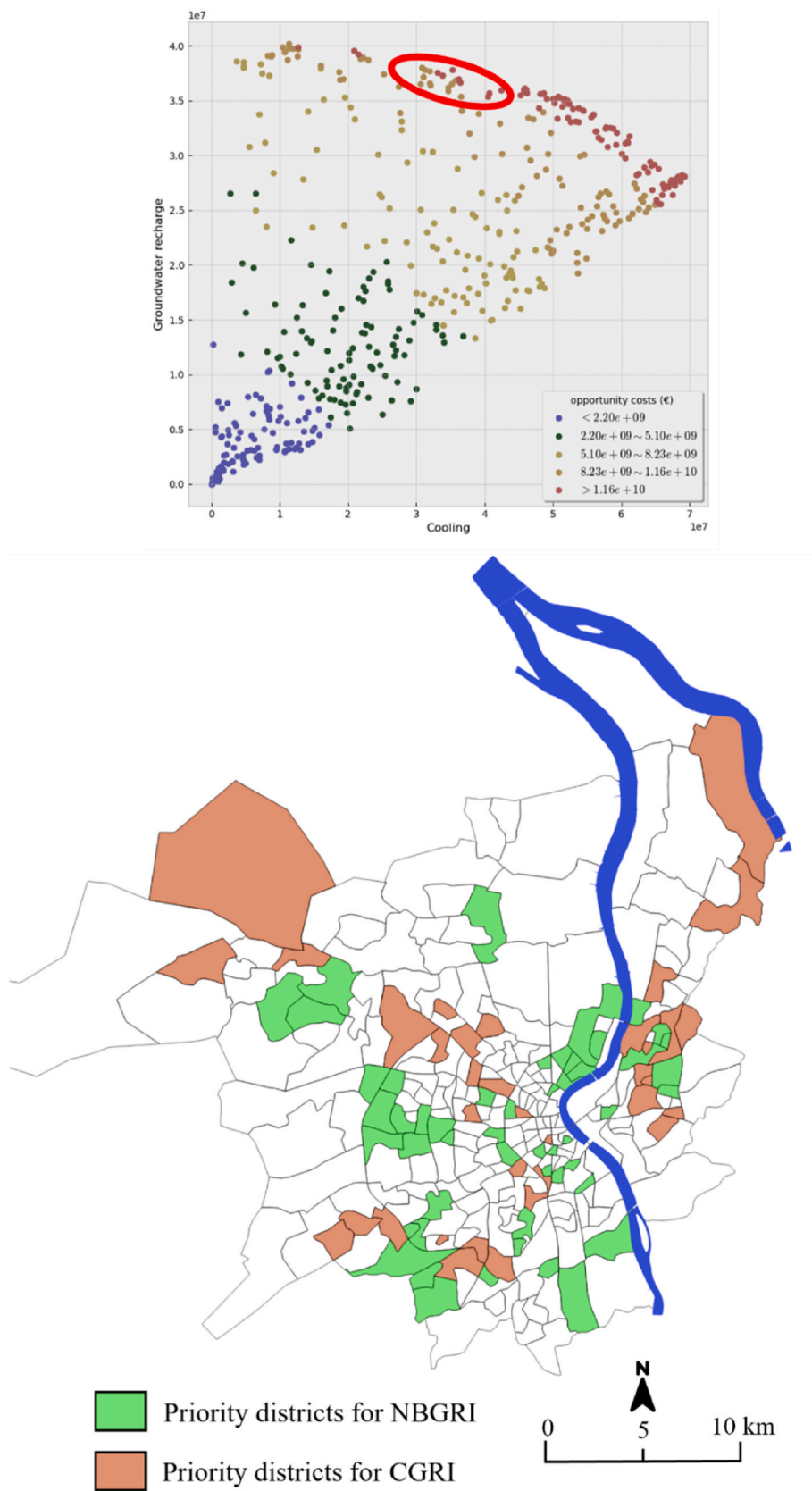


Fig. 8. Representation of solutions selected by stakeholders following the participatory process.

relatively wealthy centric districts or at newly built or under construction urban developments (Kato-Huerta and Geneletti, 2022), thus often perpetuating environmental inequities (Calderón-Argelich et al., 2021).

Interestingly, these two polar solutions do not provide a clear cut answer to the related dilemma between conventional or decentralized approaches for stormwater management (Zhang et al., 2017b). However, this MOO approach provides a spatially explicit translation of these principles, and this was perceived as a meaningful base for stakeholder interactions. Both of these polar strategies - focusing either on recharge or cooling solutions - nevertheless feature some similarities. Some districts located on the eastern bank of the city for instance are systematically selected as CGRI or as NBGR throughout the front. These sites are to be considered as sure choices for the planner. Furthermore, compromise solutions, located at intermediate points between both strategies, take from both these spatial choices, thus providing some amount of compromise in the centralized versus decentralized debate, *i. e.* hybrid solutions (D'ambrosio et al., 2021). Moving from recharge-oriented solutions towards more urban cooling-oriented solutions requires trading suburban grey infrastructure implementation for centric NBS implementation, and vice-versa.

Finally, a central result of this MOO is the presence of an area of simultaneous high environmental gains in the front: ambitious urban cooling-focused solutions tend to perform very well in terms of both benefits of recharge and cooling. This result can be of particular interest for local stakeholders as it indicates that they may not have to make a choice between focusing on either one benefit or on the other and that there may be a middle ground between conventional and decentralized scenarios. These solutions provide clear synergies, though they have the highest opportunity costs. Therefore, a critical consideration in this case study is what importance is placed on minimizing opportunity costs: if this objective is of upmost priority for stakeholders, then other solutions should be considered, while if it is not, then this particular group of solutions would be the preferred choice.

5. Perspectives and conclusions

Certain limitations of this MOO application must be acknowledged. It particularly did not consider the demand for water resources, despite water use substitution being a primary objective of the metropolitan policy. As such, the benefits from this policy would be achieved through the creation of alternative water stocks in close proximity to potential users, for watering green areas, street cleaning, industrial purposes, etc. Therefore, while the urban cooling objective took spatial demand into consideration, this approach was not extended to the recharge objective. Indeed, identifying and mapping potential demand for urban recharge across the entire city was beyond the scope of this study.

This work shows that MOO is a valuable approach to reveal and explore unknown policy options in complex urban planning problems, *e. g.* when the number of potential actions is almost infinite. MOO enables the exploration and narrowing down of potential alternatives, effectively reducing the vast number of actions, unlike MCDA or CBA. Though some MCDA incorporate a preliminary phase of identification and constitution of alternatives (Estévez and Gelcich, 2015), it is limited by the practical constraints imposed by the number of feasible comparisons. Moreover, in complex problems like the combinatorial challenge addressed in this study, it becomes exceedingly challenging to pre-determine potential optimal policy alternatives.

Nevertheless, the exploration the Pareto front is a central challenge of MOO - especially in spatial problems, and one that has been neglected in the literature. MOO can produce a very large Pareto front, whose solutions may not be immediately compared, and interpreted - in our case, spatially - to provide decision-support. Effectively identifying and categorizing the various types of solutions from the optimized front requires substantial effort. This study introduces a novel analysis approach to address this issue.

Furthermore, MOO, on its own, does not provide explicit guidance

for policy making comparable to MCDA or CBA methods. It lacks a clear signal, such as a cost-benefit ratio or stakeholder-based policy ranking, to indicate which solution should be preferred. As a result, analyzing the Pareto front requires constructing a decision narrative: identifying the main trade-offs at hand in the Pareto front, and how they may represent contrasted - and even opposing - view of the problem at hand. It can require also establishing an interpretation framework, to explain how different regions of the Pareto front correspond to distinct policy ambitions or different stages within a temporal context.

Participatory exploration of Pareto fronts resulted to offer an avenue for identifying prospective strategies to incorporate these findings into urban planning tools, specifically zoning laws. Overall, this participative process proved to be a necessary extension to the MOO to analyze the Pareto front, and single-out solutions that match with the objectives of stakeholders.

A potential future extension to this participatory process can be the interfacing of MOO and Multi-Criteria Decision Analysis, for linking the implementation of a MOO with the subsequent exploration of its outputs alongside stakeholders. MOO does not provide easy signals for the selection of a single solution. This is a complex task that has been relatively less studied. Multi-Criteria Decision Analysis, in contrast, provides a clear, participative, and tractable way of making decisions collectively, when faced with a handful of well-defined options. An interface of both approaches would result in mixing a top-down "expert" approach aiming at revealing explicitly trade-offs - here the MOO - and a simpler "turnkey" decision-making bottom-up approach - the MCDA - into the decision-making process (Alves et al., 2024; Girard et al., 2015). It would provide insights into the different preferences of stakeholders - or the public as in Estévez and Gelcich (2015), and how these differences materialize in terms of selected solutions.

The participatory workshop also led to identify several potential extensions to this work. Among these, a central one is the inventory of available plots (Fig. 3). Decision-makers highlighted that future planning tools would require even more comprehensive understanding of the nature of the available sites, *e.g.* whether these plots are publicly or privately owned. Including such considerations would allow to consider for instance how public and private entities would be mobilized with different relative intensity for implementing GRI and NBS strategies. With such an addition, the MOO would also be a way to investigate further the policy instruments required to develop GRI, for instance, monetary transfer approaches that could incentivize actors to adopt these solutions.

Overall, this study proposes an integrated approach to MOO oriented towards decision-support. It provides insights into the spatial choices and optimal strategies for developing GRI, with the objectives of maximizing groundwater recharge, maximizing urban cooling, while minimizing opportunity costs, in the context of urban climate change adaptation. The analysis of the Pareto front allows to navigate the trade-offs at play in this case study: the strong competition between opportunity costs and the other objectives, the existence of extreme points where solutions focus mostly on recharge or on urban cooling. The trade-off and participatory analysis proposed in this paper is a novel way for exploring the Pareto front, moving from aggregated results to spatially explicit results. This method can effectively inform decision-makers about the available choices, spatial strategies, and optimal planning steps, facilitating the implementation of urban groundwater recharge policies in the future.

CRedit authorship contribution statement

Georges Farina: Writing - review & editing, Writing - original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Noémie Neverre:** Writing - review & editing, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Cécile Hérviaux:** Writing - review & editing, Resources, Investigation. **Jérôme Barriere:** Writing - review &

editing, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation. **Stéphanie Pinson:** Methodology, Investigation, Formal analysis, Data curation. **Hélène Habarou:** Writing – review & editing, Supervision, Investigation, Funding acquisition, Formal analysis. **Jean-Christophe Perea:** Writing – review & editing, Supervision, Investigation, Funding acquisition, Formal analysis. **Philippe Le Coënt:** Writing – review & editing, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Georges Farina reports financial support was provided by Regional Water Agency Adour-Garonne. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jenvman.2024.123380>.

Data availability

Data will be made available on request.

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