locationallocation: solving Maximal Coverage Location-Allocation geospatial infrastructure assessment and planning problems

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Abstract

Assessing and planning infrastructure and networks over space conditional to a spatially distributed demand and with consideration of accessibility and spatial justice goals and under infrastructure allocation constraints is a key policy objective. Potential applications extend to the domains of public infrastructure assessment and planning (public services provision, e.g. transport, social services, healthcare, parks), urban environmental and climate risk reduction interventions, logistics and hubs allocation, commercial and strategic decisions. Here we introduce *locationallocation*, an R package to solve Maximal Coverage Location-Allocation problems using geospatial data in widely used R programming language geospatial libraries. The package allows to produce travel time maps and spatially optimizing the allocation of facilities in both continuous and discrete choice problems and based on spatial accessibility criteria weighted by one or more variables or a function of those. We demonstrate the use of package through an example of how it can be used to plan infrastructures that can tackle urban-scale climate risk through infrastructure assessment and spatial planning.

Software availability

The package is available at `https://github.com/giacfalk/locationallocation` and it contains the reproducible example introduced in this paper. A documenting website is also available under `https://giacfalk.github.io/locationallocation`.

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1 Introduction

Assessing and planning infrastructure and networks over space conditional to a spatially distributed demand and with consideration of accessibility and spatial justice goals and under infrastructure allocation constraints is a key policy objective Schindler and Kanai [2021], Seto et al. [2014], Todes [2012], Brown and Lloyd-Jones [2014]. This is particularly crucial in cities because the world is keeping on urbanizing (the size and share of global population classified as living in urban areas has overtaken the rural population since 2007 and it projected to increase to 68% by 2050 Urbanization Statistics [2018]).

In facility location problems, one of the most critical considerations is maximizing the coverage of demand points with a limited number of facilities. The Maximal Coverage Location-Allocation (MCLA) seeks to determine the best locations for facilities to serve the highest possible number of demand points within a predefined distance or service threshold. Church and Velle [1974] provided the first mathematical formulation of the Maximal Covering Location Problem (MCLP) to determine the best locations for facilities to maximize the coverage of demand within a given distance or time constraint.

Some of the primary reasons why MCLA problems are important include: (i) Efficient Resource Utilization: Many organizations operate with limited resources, such as emergency response units, public health clinics, or distribution centers. The MCLA problem helps optimize the placement of these resources to maximize service coverage, ensuring that the highest number of people benefit from the available facilities; (ii) Emergency Response and Public Safety: In scenarios where response time is crucial, such as ambulance or fire station placement, solving the MCLA problem can directly impact lives. By strategically locating these facilities, authorities can reduce response times and improve emergency preparedness; (iii) Retail and Service Industry Optimization: Businesses often seek to maximize their customer base while minimizing costs. Retail chains, fast-food franchises, and service providers can use MCLA models to identify optimal store locations, improving accessibility for the largest number of potential customers; (iv) infrastructure and Urban Planning: Governments and city planners use MCLA models to determine the best locations for schools, hospitals, and transportation hubs. Properly placed infrastructure ensures equitable access to essential services, reducing disparities in service distribution.

Recent work, such as Bonnet et al. [2015], demonstrated an implementation of the MCLA framework with the use of geospatial data for optimally locating automated external defibrillators (AEDs) in cities to improve emergency response times and cardiac arrest survival rates. Other studies, such as Falchetta et al. [2020] - upon which the scientific software package introduced in this paper is building - demonstrated solutions to the MCLA for healthcare facilities accessibility, a challenge which was already explored (although mostly in a descriptive rather than planning-oriented lens, by Weiss et al. [2020]). Their framework is implemented with spatially-explicit data on factors such as population density, historical cardiac arrest data, and accessibility constraints. However, irrespective of such previous work implementing the domains of data science and the solution to problem such as MCLA (see the review of Chen and Murray [2021]), existing open-source implementations in R are limited to *traveltime* [Ryan et al., 2025], which is suitable to calculate descriptive snapshots and maps, the *maxcovr* [max, 2025] package (`https://github.com/njtierney/maxcovr`) which however is not implemented in a way to be integrated with R's geospatial data processing capabilities.

In this paper, I introduce the *locationallocation* R package, which allows spatially optimizing the allocation of facilities and infrastructure based on spatial accessibility criteria weighted by one or more variables or a function of those. In *locationallocation*, such maximization can be modified to e.g. minimize risk (exposure of the population times environmental hazard), even considering population-specific vulnerability (age, health status, other geographical features). I demonstrate the package with a use case on how to tackle urban-scale climate risk through infrastructure assessment and spatial planning.

The remainder of the paper is structured as follows: in Section 2 we provide a concise mathematical formulation of the MCLP problem and of its solution algorithm; then we discuss the software and data implementation that underlie the *locationallocation* R package. In Section 3 we present an use of the package based on sample data and objectives. We conclude in Section 4 with a commentary on the potential use cases of the package, as well as its current limitation and potential for future further developments.

2 Methods and data

Maximal Coverage Location Problem (MCLP)

Before introducing the software implementation and the functioning of the *locationallocation* package, it is worth providing a concise mathematical formulation of the class of problems addressed by the package.

Sets and Indices:

- I : Set of candidate facility locations ($i \in I$).
- J : Set of demand points ($j \in J$).

Parameters:

- w_j : Population (or demand weight) at location j.
- d_{ij} : Travel time from facility location i to demand point j.
- T : Maximum acceptable travel-time threshold for coverage.
- $N_j = \{i \in I \mid d_{ij} \leq T\}$: Set of candidate facilities that can cover demand point j.
- *Optionally,* $P^{(\star)}$: Maximum number of facilities to be located from a discrete set of pre-defined locations P on the lattice space.

Decision Variables:

- $x_i \in \{0, 1\}$: 1 if a facility is located at site i, 0 otherwise.

- $y_j \in \{0, 1\}$: 1 if demand point j is covered by at least one facility, 0 otherwise.

Objective Function: Maximize the total covered population:

$$\max \sum_{j \in J} w_j y_j \tag{1}$$

Constraints:

1. Coverage constraint: A demand point j is covered if at least one facility in N_j is selected:
$$y_j \leq \sum_{i \in N_j} x_i, \quad \forall j \in J \tag{2}$$

2. Binary constraints:
$$x_i \in \{0, 1\}, \quad \forall i \in I \tag{3}$$

$$y_j \in \{0, 1\}, \quad \forall j \in J \tag{4}$$

   and, optionally:

3. Facility location constraint (at most $P^{(}\star)$ facilities must be chosen from a discrete set of pre-defined locations P on the lattice space):
$$\sum_{i \in I} x_i \leq P^{(}\star) \tag{5}$$

Problem solution algorithm

Greedy Heuristic are used to identify quasi-optimal solution without resorting to resource and time-intensive constrained optimization approaches such as Mixed-Integer Programming (MIP):

In the heuristics, to choose the location of the next facility allocation, two approaches are implemented:

- Allocation based on maximum demand weight location at each iteration k
- Allocation based on maximum value of spatial kernel density map (using a kernel function to fit a smoothly tapered surface to each point) of demand weights location at each iteration k

In the case of a discrete set of potential allocation sites, a random sampling approach is adopted, where the accessibility algorithm is implemented r times, in each of which a set of $P*$ locations is drawn and the global demand coverage based on such facilities is calculated at the end of each iteration to gauge the best performing set of facilities in the discrete number of sets drawn from the discrete set of all the combinations of size $P*$ among the P global set of candidate facilities.

Algorithm 1 Greedy Heuristic for MCLP over continuous lattice space

Require: Set of candidate facility locations I, set of demand points J, travel-time matrix d_{ij}, population weights w_j, number of facilities P, coverage threshold T.

Ensure: A set S of selected facility locations.

Initialize $S \leftarrow \emptyset$ ▷ Set of selected facilities

Initialize $J_{\text{unmet}} \leftarrow J$ ▷ Set of unmet demand points

for $k = 1$ to $P* \in P$ **do**

  Find the facility i^* that maximizes covered demand:

$$i^* = \arg\max_{i \in I \setminus S} \sum_{j \in J_{\text{unmet}}} w_j \mathbb{1}(d_{ij} \leq T)$$

  Add i^* to the selected facilities: $S \leftarrow S \cup \{i^*\}$

  Update covered demand points:

$$J_{\text{unmet}} \leftarrow J_{\text{unmet}} \setminus \{j \mid d_{i^*j} \leq T\}$$

end for

return S

Software and data implementation

The approach includes consideration of different travel modes and can be applied to any location in the world. A spatial statistical downscaling ("disseving") approach for the underlying friction surface data based on street network data from Open Street Map API is embedded in the package to perform location-allocation spatial optimization at a high spatial-resolution (particularly useful in urban-scale applications). A set of reporting functions and graphical outputs are pre-calculated as part of the package. The package relies on *malariaAtlas*, *dissever* and *gdistance* functions, as well as on *raster*, *terra*, and *sf* classes od object.

- **Friction layers:** Malaria Atlas friction surfaces: walking or fastest mode
- **Point locations of existing facilities:** A point simple feature geometry (sf)
- **Point locations for candidate facilities:** Optional, point simple feature geometry (sf)
- **Demand weights:** A raster. It can be, for instance, population counts per location (grid cell), optionally in a weighted form by specifying the *weights* argument to another raster. This would allow using a risk framework where the demand is defined as a risk map R of:

  $R = POP \times HAZARD \times VULNERABILITY$

The package core functions are the following:

```
traveltime(facilities, bb_area, dowscaling_model_type, mode, res_
   output = 100)
```

The *traveltime* function generates a travel time map based on the input facilities, bounding box area, and travel mode, having the following arguments:

- *facilities*: A sf object with the existing facilities.
- *bb_area*: A boundary box object with the area of interest.
- dowscaling_model_type: The type of model used for the spatial statistical downscaling of the travel time layer.
- *mode*: The mode of transport.
- *res_output*: The spatial resolution of the friction raster (and of the analysis), in meters. If <1000, a spatial statistical downscaling approach is used.

```
allocation(demand_raster, traveltime_raster = NULL, bb_area,
    facilities = facilities, weights = NULL, objectiveminutes = 10,
    objectiveshare = 0.99, heur = "max", dowscaling_model_type, mode,
    res_output)
```

The *allocation* function is used to allocate facilities in a continuous location problem. It uses the accumulated cost algorithm to find the optimal location for the facilities based on the demand, travel time, and weights for the demand, and target travel time threshold and share of the demand to be covered, having the following arguments:

- *demand_raster*: A raster object with the demand for the service.
- *traveltime_raster*: The output of the traveltime function. If not provided, the function will run the traveltime function first.
- *bb_area*: A boundary box object with the area of interest.
- *facilities*: A sf object with the existing facilities.
- *weights*: A raster with the weights for the demand.
- *objectiveminutes*: The objective travel time in minutes.
- *objectiveshare*: The share of the demand to be covered.
- *heur*: The heuristic approach to be used. Options are "max" (default) and "kd".
- *dowscaling_model_type*: The type of model used for the spatial statistical downscaling of the travel time layer.
- *mode*: The mode of transport.
- $res_o utput$: The spatial resolution of the friction raster (and of the analysis), in meters. If <1000, a spatial statistical downscaling approach is used.

```
allocation_discrete(demand_raster, traveltime_raster = NULL, bb_area,
    facilities = NULL, candidate, n_fac = Inf, weights = NULL,
    objectiveminutes = 10, dowscaling_model_type, mode, res_output, n_
    samples)
```

The $allocation_discrete$ function, having the following arguments:

- *demand_raster*: A raster object with the demand for the service.
- *traveltime_raster*; The output of the traveltime function. If not provided, the function will run the traveltime function first.
- *bb_area*: A boundary box object with the area of interest.
- *facilities*: A sf object with the existing facilities.
- *candidate*: A sf object with the candidate locations for the new facilities.
- *n_fac*: The number of facilities that can be allocated.
- *weights*: A raster with the weights for the demand.
- *objectiveminutes*: The objective travel time in minutes.
- *dowscaling_model_type*: The type of model used for the spatial statistical downscaling of the travel time layer.
- *mode*: The mode of transport.
- *res_output*: The spatial resolution of the friction raster (and of the analysis), in meters. If $<$1000, a spatial statistical downscaling approach is used.
- *n_samples*: The number of samples to generate in the heuristic approach for identifying the best set of facilities to be allocated.

Ancillary functions include *allocation_plot*(), *demo_data_load*(), *friction*(), *mask_raster_to_polygon*(), *traveltime_plot*(), and *traveltime_stats*(), and they are documented in the package repository and vignette website.

3 Use case: optimal allocation of public water fountains with consideration of heat hazard, exposure, and vulnerability

The world is experiencing climate change impacts (climate impacts are becoming ever more frequent and severe for both citizens and governments across a range of dimensions, including socio-economic outcomes, human health, and environmental systems). Hence, evaluating the public provisions of infrastructure that can support adaptation to different climate hazards and impacts at the urban scale has crucial implications for acting to reduce the adversity and inequity of climate change impacts. Such knowledge can be used to inform the design and transformation of urban areas into more climate-resilient, just, sustainable living systems.

As a use case, we evaluate accessibility and optimize accessibility goals to public drinking water fountains in the city of Naples, Italy with consideration of exposure (population density), hazard (average number of days per year with a local Wet-Bulb Globe Temperature $> 25^\circ$ C, and vulnerability (poverty map).

First, we obtain water fountain coordinate location for city from the Open Street Maps API using the *osmdata* package using the query $amenity = drinking_water$. We also obtain gridded population data at a 100m spatial resolution from GHS-POP data product Florczyk et al. [2019], a urban microclimate model output for historical Wet-Bulb Globe Temperature from the UrbClim model Lauwaet et al. [2024], and the administrative boundaries of the city of Naples from the Eurostat's LAU database, as depicted in Figure 1. The following example datasets are fully embedded in the package and they become available in the R global environment by calling the *demo_data_load* function.

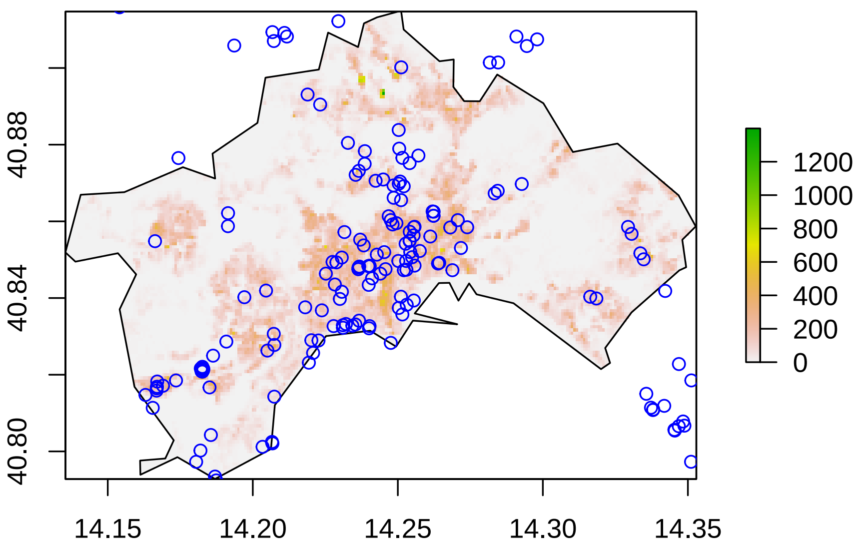

Figure 1: Map of population density and location of public drinking water fountains in Naples, Italy.

Then, we implement the *traveltime* function to calculate a map of accessibility to public drinking water sources as follows:

```
out_tt <- traveltime(facilities=fountains, bb_area=boundary,
    dowscaling_model_type="lm", mode="walk", res_output=100)
```

The function yields a raster output which - for each pixel - shows the estimated travel time to reach the most accessible facility (nearest in travel time terms) for the selected travel mode. The resulting layer can be visualized via:

```
traveltime_plot(traveltime=out_tt, bb_area=boundary, facilities =
    fountains)
```

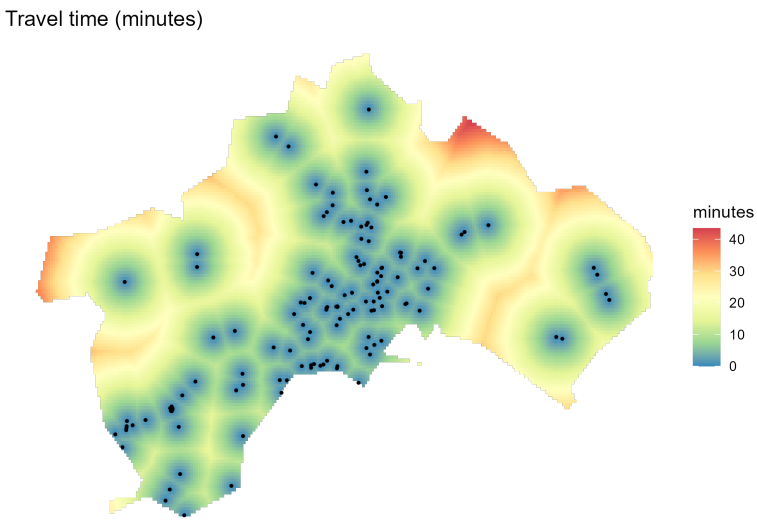

Figure 2: Map of the walking travel time to the nearest public drinking water fountain in Naples, Italy.

We can also produce a summary plot and statistic based on the output of the *traveltime* function and a given demand (e.g., population) raster, as well as a given time threshold parameter:

```
traveltime_stats(traveltime = out_tt, demand_raster = pop, breaks=c(5,
    10, 15, 30), objectiveminutes=5)
```

yielding:

```
[1] "38.54 % of demand layer within the objectiveminutes threshold."
```

We then can proceed optimize allocation of new water fountains to cover maximum fraction of (unweighted) population. Location-allocation can be either solved discretely or continuously over space, and either with a facility constraint or with a policy goal for demand (population) coverage. For instance, if the goals is to optimise allocation of new water fountains to cover maximum fraction of heat-risk weighted population (exposure), we can use:

```
output_allocation <- allocation(demand_raster = pop, traveltime_raster
   =out_tt, bb_area = boundary, facilities=fountains, weights=NULL,
   objectiveminutes=15, objectiveshare=0.01, heur="max", dowscaling_
   model_type="lm", mode="walk", res_output=100)

allocation_plot(output_allocation, bb_area = boundary)
```

This yields an output object containing both the coordinate location of the allocated facility to meet the accessibility objectives, and the updated travel time map:

Figure 3: Map of the continuous location-allocation problem solution for a 15-minute walk and a 99% demand coverage objective for the nearest public drinking water fountain in Naples, Italy.

If we use demadn weights (e.g. maximum temperature), we can use:

```
output_allocation_weighted <- allocation(demand_raster = pop,
    traveltime_raster=out_tt, bb_area = boundary, facilities=fountains
    , weights=hotdays, objectiveminutes=15, objectiveshare=0.01, heur=
    "max", dowscaling_model_type="lm", mode="walk", res_output=100)

allocation_plot(output_allocation_weighted, bb_area = boundary)
```

where *tmax* is a raster layer matching the extent, spatial resolution of the *pop* demand raster. We can notice how results change when using such weighted approach:

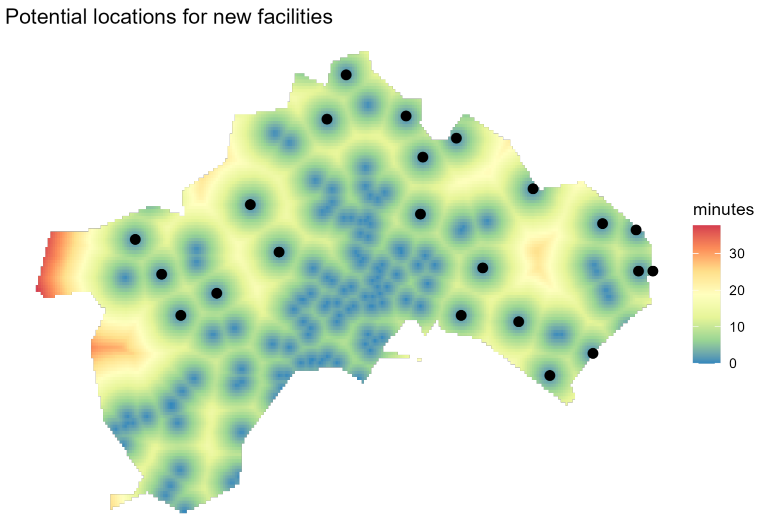

Figure 4: Map of the continuous location-allocation weighted problem solution for a 15-minute walk, a 99% demand coverage objective, and a demand weight based on the frequency of hot days for the nearest public drinking water fountain in Naples, Italy.

Otherwise, if we want to prioritize among a discrete set of pre-defined potential sites (e.g. sites along the water pipes network), we can use:

```
candidates <- st_sample(boundary, 30)

output_allocation_discrete <- allocation_discrete(demand_raster = pop,
     traveltime_raster=NULL, bb_area = boundary, facilities=fountains,
     candidate=candidates, n_fac = 10, weights=NULL, objectiveminutes
    =15, dowscaling_model_type="lm", mode="walk", res_output=100, n_
    samples=100)

allocation_plot_discrete(output_allocation_discrete, bb_area =
    boundary)
```

The resulting map shows the coordinate location of the selected facilities among the candidate set (subject to the number of facilities constraint), with the title of the plot reporting the demand coverage rate attained:

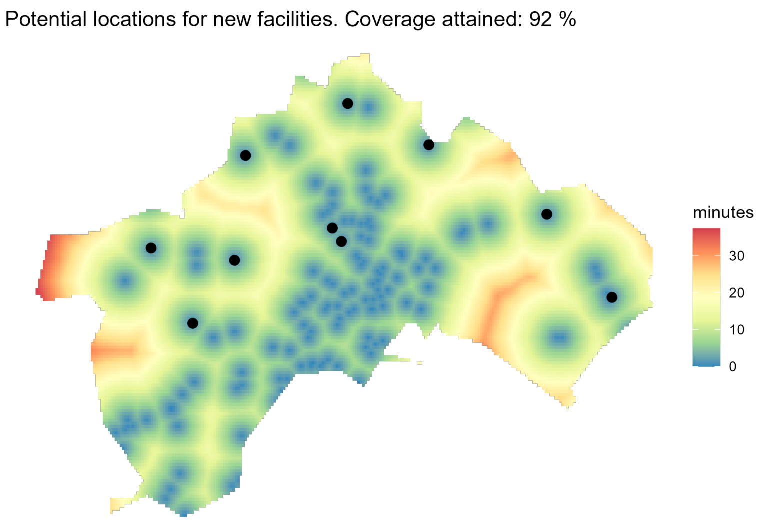

Figure 5: Map of the discrete location-allocation problem solution for a 15-minute walk and a 99% demand coverage objective for the nearest public drinking water fountain in Naples, Italy.

Note that it is also possible to solve location-allocation problems from scratch, i.e. in the absence of pre-existing facilities:

```
set.seed(333)

output_allocation_discrete_from_scratch <- allocation_discrete(demand_
    raster = pop, traveltime_raster=NULL, bb_area = boundary,
    facilities=NULL, candidate=candidates, n_fac = 10, weights=NULL,
    objectiveminutes=15, dowscaling_model_type="lm", mode="walk", res_
    output=100, n_samples=100)

allocation_plot_discrete(output_allocation_discrete_from_scratch, bb_
    area = boundary)
```

Also in this case, the resulting map shows the coordinate location of the selected facilities among the candidate set (subject to the number of facilities constraint, with the title of the plot reporting the demand coverage rate attained). We can note that in this case the travel time layer is computed from scratch, rather than updated:

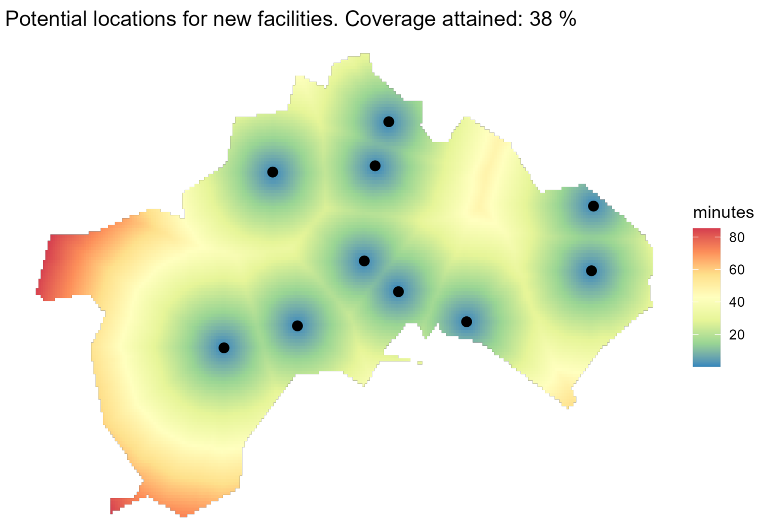

Figure 6: Map of the discrete location-allocation problem solution for a 15-minute walk and a 99% demand coverage objective and in a case of absence of pre-existing facilities in Naples, Italy.

4 Discussion and conclusion

This paper provides an illustration of the theoretical background, the software and data implementation, and the use case for the *locationallocation* R package. The suite of functions in the package are suitable to be applied to geographical location-allocation problems, such as (but not only) in cities. Example applications in the domain of urban environmental and climate risk include cooling centers, green space, emergency services, drinking water, transport, or flood protection infrastructure. Beyond, other domains of application include public infrastructure assessment and planning (public services provision, e.g. transport, social services, healthcare, parks), logistics and hubs allocation, commercial and strategic decisions.

Despite the advancements brought by *locationallocation* in its capacity to bridge the mathematical formulation of the MCLA problem with the application with geospatial data and libraries in the R scientific programming language, the package has limitations. For instance currently, the package does not support facility-level attributes that can affect the location allocation or local density or size of the facility to be allocated (e.g. supply constraints such as beds per hospital or users per facilities), as all facilities are equally defined. Moreover, the apporach to establish the location of the next facility to be allocated in the lattice space (in the continuous allocation problem) or the exact set of facilities optimizing the objective (in the discrete allocation problem) is currently based on heuristics which might not necessarily coincide with the single (if uniquely identified) globally optimal solution. Such heuristics are based on the selection of the highest demand or spatial kernel density of demand pixel where accessibility objectives are not yet satisfied at each iteration i, or - in the discrete problem case - on the number of random sets of facilities of size n that are sampled and evaluated among the global set of candidate facilities of size N. The identification of a truly global optimal solution would however require the development of a constrained optimization framework requiring the use of computationally intensive professional solvers. Future software work might implement such features and expand the package capabilities.

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