ediblecity: an R package to model and estimate the benefits of urban agriculture

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## Abstract

Urban agriculture is gaining attraction to become one of the pillars of the urban ecological transition and to increase food security in an urbanized planet. However, there is a lack of systematic quantification of the benefits provided by urban agriculture solutions. In this paper, we present an R package to estimate several indicators related to benefits of urban agriculture. The goal is to provide a tool for researchers and practitioners interested in the impacts of urban agriculture. The ediblecity package provides functions to calculate 8 indicators: urban heat island, runoff prevention, green areas accessibility, NO2 sequestration, jobs created in commercial gardens, volunteers involved in community gardens, green per capita and, finally, food production. Moreover, the package also provides a function to create scenarios with different implementations of urban agriculture. We illustrate the use of the package by comparing three scenarios in a neighborhood of Girona (Spain), which is included in the package as an example dataset. There, we compare scenarios with an increasing amount of urban agriculture solutions. The ediblecity package is open-source software. This allows other R developers to contribute to the package providing new functionalities or improving the existing ones.

**Keywords:** edible city solutions; urban farming; urban food; nature-based solutions; Rstats; urban challenges; societal challenges; urban agriculture

# Introduction

Urban agriculture is becoming one of the pillars of the urban ecological transition (Säumel, Reddy, and Wachtel 2019). Likewise, urban agriculture might have a key role ensuring food security in an urbanized planet (Barthel, Parker, and Ernstson 2015). As a consequence, some research has paid attention on the actual or potential food production of urban agriculture (Grafius et al. 2020; Richardson and Moskal 2016). However, some others authors argued that the importance of urban agriculture does not reside in their ability to produce food but in the social benefits it provides, such as public health (Soga et al. 2017) and social cohesion (Säumel, Reddy, and Wachtel 2019). Moreover, other authors stated that urban agriculture can provide environmental benefits as well, such climate regulation (Clinton et al. 2018) or water runoff prevention (Gittleman et al. 2017).

However, there is a lack of systematic quantification of the benefits provided by urban agriculture (Langemeyer et al. 2021a). For instance, there is no clear evidence to what extent urban agriculture could contribute to reduce the urban heat island (Lin, Philpott, and Jha 2015) or to a greener economy (Säumel, Reddy, and Wachtel 2019). However, most studies have been focused on a single initiative and one benefit (Artmann and Sartison 2018).

Therefore, decision-makers, who are responsible of leading the urban transitions to more sustainable and resilient cities, are orphan of evidence in how to implement urban agriculture to maximize its impact on sustainability. Yet, several studies provided some insights that can guide the implementation of urban agriculture. For instance, some models explore the rainwater harvesting potential of urban agriculture (Gittleman et al. 2017; Lupia et al. 2017). Broader, G’omez-Villarino and Ruiz-Garcia (2021) developed guidelines to maximize ecosystem services through urban agriculture by applying adaptive design and providing a battery of indicators. And, as expected, many models have been developed to quantify food production and food security provided by urban agriculture by simulating a myriad of scenarios with different types of urban agriculture virtually implemented such as rooftop gardens, community gardens or private citizen-led gardens (Grafius et al. 2020; Grewal and Grewal 2012; Hsieh, Hsu, and Lee 2017; MacRae et al. 2010). Yet, a transferable model (applicable to any city) to assess simultaneously several environmental and social benefits is lacking.

Hence, our goal is to provide a tool to estimate those multiple benefits of urban agriculture that help decision-makers to strategically implement urban agriculture solutions. We developed the estimations for eight indicators measuring urban agriculture benefits and a functionality to create scenarios of urban agriculture based on the proportion of elements to be transformed to urban agriculture and on which elements will be transformed. Likewise, we packed all those functionalities in an R package called ediblecity. In the methods, we present the interface of the package and then we illustrate the usefulness by applying the model in a neighborhood of Girona (Spain).

# Methods

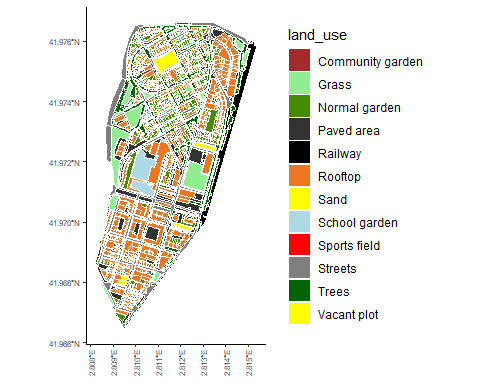
## Implementation: the model under the package

All the equations and algorithms to model the benefits of urban agriculture were encapsulated in an R package (R Core Team 2022), using one function for each indicator and one function to create scenarios. The package was created using R version 4.2.1 (R Core Team 2022) in RStudio desktop v. 2022.07.02. The package structure was assisted by the package devtools (Wickham, Hester, et al. 2022) following the principles in Wickham and Bryan (2022). Likewise, the documentation of the functions was assisted by the package roxygen2 (Wickham, Danenberg, et al. 2022). The dependencies of the package are:

* dplyr (>= 1.0.6) (Wickham, François, et al. 2022)
* magrittr (>= 2.0.1) (Bache and Wickham 2022)
* sf (>=0.9) (Pebesma 2018a)
* stars (>= 0.5) (Pebesma 2022)
* rlang (>= 1.0) (Henry and Wickham 2022b)

### Urban representation of the city of interest

The ediblecity package provides 8 functions to estimate 8 different indicators and a function to generate scenarios. It takes as a basis a spatial representation of a city (or a part of a city) as a GIS layer. This representation must have one attribute indicating the land uses of the city, such as gardens, streets, rooftops, etc. Some indicators require specific information to be included in the representation. These is explained in each indicator’s section.



The package includes the representation of Sant Narcís, a neighbourhood of Girona (Spain) as an example of an urban representation (Figure 1). This example can help the users to create the representation of their cities of interest. In the table below, a sample with one element of each type is shown. The representation is provided as an sf object, which is a class for spatial data in R implemented by package sf (Pebesma 2018b)

Structure of the urban representation example

| Column | Description |
| --- | --- |
| land\_use | A category representing the urban elements |
| land\_use\_verbose | A more detailed category for the element, for example, if it is residential |
| floors | The number of floors of the element, 0 for non-built |
| area | The surface of the element |
| flat\_area | The surface of the element that is flat (slope < 5º) |
| edible\_area | The surface that is used to grow edible plants. Only applicable to urban agriculture solutions |

Along with the example for an urban representation, the ediblecity package also includes a data.frame with the general attributes of each green typology in the urban representation used to estimate the indicators (Table 2). However, the user can provide their own attributes to estimate any indicator. In city\_land\_uses there are other columns not shown in table 2, they are logical variables (i.e. TRUE/FALSE) used internally by the package to select urban agriculture elements.

pGreen is the proportion of green of the urban element. In urban agriculture solutions, this is overriden by the attribute edible\_area. The following attributes come in pairs. This is to consider uncertainty in the estimations. The functions use a random value within the range provided by the pair of values for each element in the city. no2\_seq is the capacity of the element to capture NO2 in gr/s. food is the food productivity in kg/m2 and CN is their curve number, used to calculate infiltration rates (Cronshey, Roberts, and Miller 1985).

General attributes of the elements of urban green used to estimate the indicators

| land\_uses | pGreen | no2\_seq1 | no2\_seq2 | food1 | food2 | CN1 | CN2 |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Edible private garden | 0.6 | 0.07 | 0.09 | 0.2 | 6.6 | 85 | 88 |
| Community garden | 1.0 | 0.07 | 0.09 | 0.2 | 2.2 | 85 | 88 |
| Commercial garden | 1.0 | 0.07 | 0.09 | 4.0 | 6.6 | 85 | 85 |
| Rooftop garden | 1.0 | 0.07 | 0.07 | 0.2 | 2.2 | 67 | 88 |
| Hydroponic rooftop | 1.0 | 0.07 | 0.07 | 9.0 | 19.0 | 98 | 98 |
| Arable land | 0.6 | 0.00 | 0.07 | 4.0 | 6.6 | 85 | 88 |
| Normal garden | 0.6 | 0.07 | 0.07 | 1.0 | 1.0 | 74 | 86 |
| Permanent crops | 0.6 | 0.09 | 0.09 | 4.0 | 6.6 | 65 | 77 |
| Vacant | 1.0 | 0.07 | 0.09 | 1.0 | 1.0 | 74 | 87 |
| Grass | 1.0 | 0.07 | 0.07 | 1.0 | 1.0 | 74 | 86 |
| Mulcher | 1.0 | 0.00 | 0.00 | 1.0 | 1.0 | 88 | 88 |
| Raised bed | 1.0 | 0.07 | 0.07 | 1.0 | 1.0 | 67 | 88 |
| Trees | 1.0 | 0.11 | 0.11 | 1.0 | 1.0 | 70 | 77 |
| Vegetated pergola | 1.0 | 0.07 | 0.07 | 1.0 | 1.0 | 98 | 98 |

### Indicators estimated

#### Urban heat island

The urban heat island is a measure of how urban agriculture can contribute to climate change adaptation (Langemeyer et al. 2021b). The indicator uses the equation developed by Theeuwes et al. (2017), which was validated in 14 cities. It calculates the difference in air temperature between the urban street canyon and the rural environment. To calculate this indicator, the user must provide a raster representing the sky view factor (SVF), which describes the proportion of the unobstructed hemisphere above a certain location. SAGA, a collection of open-source algorithms for geocomputation, provides an algorithm to calculate the SVF (Conrad 2008).

where is the proportion of vegetation in cell ; is the daily average global radiation (in W/m2/hour); is the air heat capacity (in J); is air density (in kg/m3); is the difference between the maximum and minimum daily average temperatures (in ºC); and is the daily average wind speed (in m/s).

The indicator to estimate the urban heat island is implemented by the package under the function UHI. The user must provide the urban representation (x) and the raster with SVF values (SVF). The green\_df argument is a data.frame with the proportion of green of each element (land\_use) in the urban representation. All the meteorological arguments are provided by default, based on the example provided (Mediterranean climate). However, the user can override them to provide values of their city of interest.

The function returns by default a summary of statistics of the UHI in x (min, 25%, 50%, mean, 75% and max values). If the argument return\_raster is set to TRUE, the function returns a raster as stars object (Pebesma 2021) with the UHI values. If verbose is set to TRUE, then the function returns a vector (i.e. an array) with the UHI in each cell. Both use the same resolution than SVF.

Code snippet 1: Function and arguments to estimate urban heat island.

UHI(  
 x,  
 SVF,  
 green\_df = NULL,  
 Qql = 6.11,  
 Cair = 1007,  
 Pair = 1.14,  
 Tmax = 30.8,  
 Tmin = 20,  
 windspeed = 2.77,  
 return\_raster = FALSE,  
 verbose = FALSE  
)

#### Runoff prevention

Surface runoff is the flow of water occurring on the ground surface when excess rainwater can no longer sufficiently rapidly infiltrate in the soil. Hence, runoff mitigation contributes to climate resilience since rain events will increase due to climate change (Shukla et al. 2019). The indicator measures the runoff in the city after a specific 24-hours rain event as well as the amount of rainwater harvested by harvesting systems. We departed from the model developed by the Soil Conservation Service (USDA), known as SCS runoff curve number method (Cronshey, Roberts, and Miller 1985).

where is the rainfall volume in mm; is the initial abstraction (all losses before runoff begins); and is the potential soil moisture retention, which is a function of the curve number (which is detemined by hydrologic soil group, see Cronshey, Roberts, and Miller (1985) for more details on the method). The SCS generalizes as , we modified this generalization to include the rainwater harvested:

where is the potential water harvested by the element , calculated as the amount of water fallen on the surface of adjacent higher buildings that are not used for gardening (in litres); is the water storage capacity of the element in terms of tank volume (in litres). From both, the minimum is used to calculate .

The runoff\_prev function estimates the runoff (in mm) as well as the total rainfall in x and the total rainwater harvested. Along with the urban representation (x), the user must provide a data.frame with the functions, two columns representing the range of curve numbers and a logical column indicating if the element (a urban garden, a building,…) has potential to harvest rainwater. The argument rain allows to set the rain event (in mm), which must be defined by the user. The curve number of each element is randomized within this range provided in runoff\_df. If runoff\_df is not provided, city\_land\_uses is used instead. Following, floors\_field is the name of attribute in x that specifies the number of floors of each element; harvest\_dist is the maximum distance to consider that a building is adjacent to the element; and tank\_size is a range for the volume of the rainwater tank (in m3). The volume of each tank in the city is randomized within this range. All randomizations follow a random uniform distribution within the correspondent range.

Code snippet 2: Function and arguments to estimate runoff prevention

runoff\_prev(  
 x,  
 runoff\_df = NULL,  
 rain = 85,  
 floors\_field = "floors",  
 harvest\_dist = 10,  
 tank\_size = c(0, 45)  
)

#### Green areas accessibility

This indicator calculates the distance from each home to the closest public green area and return a summary of statistics (min, 25%, 50%, mean, 75% and max). It includes the possibility to exclude areas smaller than a threshold. The function to calculate these distances is green\_distance. It requires, as usual, the urban representation (x) and a vector with all the categories considered public green areas. If it is not provided, the function uses the categories from city\_land\_uses where the attribute public is TRUE. The argument residence\_col indicates the variable of the urban representation (x) that must be used to identify the residences. Subsequently, residences indicates which categories of residence\_col must be considered. The min\_area argument can be used to exclude smaller areas than the value passed to the function (the threshold mentioned above).

If percent\_out is set to TRUE, the function returns the percentage of houses that are further than max\_dist argument from their closest public green area (excluding areas smaller than min\_area). The default values for min\_area and max\_dist follow the recommendations of the World Health Organization, who recommended that all residences should be closer than 300 meters from a public green area larger than 0.5 ha.

Finally, if verbose argument is set to TRUE, a vector with all distances is returned.

Code snippet 3: Function and arguments to calculate green accessibility

green\_distance(  
 x,  
 green\_cat = NULL,  
 residence\_col = "land\_use\_verbose",  
 residences = "Residence",  
 min\_area = 5000,  
 percent\_out = FALSE,  
 max\_dist = 300,  
 verbose = FALSE  
)

#### Nitrogen dioxide sequestration

Nitrogen dioxide is a good proxy of overall air quality (Mayer 1999) and one of the most concerning issues in cities, with important consequences on respiratory diseases and lung cancer (Kampa and Castanas 2008). This indicator calculates the amount of NO2 sequestered by urban green and urban agriculture solutions (in g/s).

where is the area (in m2) of the element ; and is the capacity of element to sequester NO2 (in g/s).

The function to estimate the NO2 sequestered is no2\_seq. It has only two arguments; the urban representation (x) and a data.frame with four columns:

* land\_uses: Column with the function to be considered in the calculations corresponding to land\_use attribute in x.
* no2\_seq1: The low range of NO2 sequestration of each function (in g/s/m2).
* no2\_seq2: The high range of NO2 sequestration of each function (in g/s/m2).
* pGreen: The proportion of green surface in each function.

The capacity ( in the previous equation) of each element is randomized within the range provided by no2\_seq1 and no2\_seq2. As well the area of each element is multiplied by pGreen. In urban agriculture solutions, the attribute edible\_area overrides the more general pGreen.

Code snippet 4: Function and arguments to calculate NO2 sequestration

no2\_seq(x, green\_df = NULL)

#### Jobs created and volunteers involved

Two indicators are proposed to account for the hours of work in the ECS. One indicator relates to volunteers time and the other one relates to time of new workers (jobs created). When the urban agriculture solutions are community solutions they need volunteers to be involved. On the other hand, when they are for commercial purposes, they are supposed to create jobs. Both indicators use the same equation:

where is the area in m2 used to grow plants (edible\_area) in the element ; and is the number of jobs or volunteers by m2. In both functions, is sampled from a random uniform distribution within the specified range. Then, a Monte Carlo simulation of 1,000 iterations is executed to estimate the confidence interval.

The functions to calculate these indicators are edible\_jobs and volunteer\_jobs respectively. They share the same arguments, expect for jobs and volunteers, which is the value of in the previous equation. As usual, the first argument is the urban representation (x), the attribute of x defining the area used to grow plants is are\_col, the confidence interval is defined in interval, and if verbose is set to TRUE, instead of the confidence interval, the function returns a vector of length 1,000 with all the results of the Monte Carlo simulation.

Code snippet 5: Function and arguments to calculate number of jobs created and volunteers involved in urban agriculture.

edible\_jobs(  
 x,  
 jobs = c(0.000163, 0.022),  
 edible = NULL,  
 area\_col = "edible\_area",  
 interval = 0.95,  
 verbose = FALSE  
)  
  
edible\_volunteers(  
 x,  
 volunteers = c(0.00163, 0.22),  
 edible = NULL,  
 area\_col = "edible\_area",  
 interval = 0.95,  
 verbose = FALSE  
)

#### Green per capita

We propose an indicator to estimate green per capita at neighborhood level and at city level, including public and private gardens to account for environmental justice (Kabisch and Haase 2014). At the neighborhood level a ratio between the most and least green neighborhoods is calculated. Moreover, since wealthier areas tend to have more private gardens (Farahani, Maller, and Phelan 2018), these can be included in the account of green per capita to not underestimate green per capita in those neighbourhoods.

The function to calculate this indicator is green\_capita. Along with the urban representation (x). As in other functions, the green\_categories argument in the function is a list of the categories to be considered as green areas. To calculate the green per capita in the overall city, the user must provide the number of inhabitants in inhabitants. There are two options to calculate green per capita at a neighbourhood level. The urban representation can contain two variables indicating the neighbourhoods and the inhabitants (specified in name\_col and inh\_col arguments respectively). Or the user can provide a GIS layer with the neighbourhoods’ boundaries and their attributes.

Furthermore, when the private argument is set to TRUE, the private gardens are also considered. Alternatively, the user can provide a list of elements to be considered as private green areas (e.g. parks, urban gardens,…). When the argument verbose is set to TRUE, the function returns the green per capita in each neighbourhood instead of the ratio between the most and least green ones. Finally, the argument min\_inh is to exclude neighbourhoods whose number of inhabitants is under a threshold to avoid the bias in green per capita due to unpopulated neighbourhoods (e.g. industrial districts).

Code snippet 6: Function and arguments to calculate green per capita.

green\_capita(  
 x,  
 green\_categories = NULL,  
 inhabitants = NULL,  
 neighbourhoods = NULL,  
 name\_col = NULL,  
 inh\_col = NULL,  
 private = FALSE,  
 verbose = FALSE,  
 min\_inh = 0  
)

#### Food production

Although many authors stated that the main goal of urban agriculture is not to produce food (Säumel, Reddy, and Wachtel 2019; Tornaghi 2012), food production is undoubtedly an important component of urban gardens (Furness and Gallaher 2018; Steel 2008) and the most frequent output modeled at a city scale (Grafius et al. 2020; Grewal and Grewal 2012). The food production is measured in terms of productivity:

where is the yield (in ) of the category of urban garden; and is the area of urban garden in . By default, the value of is randomized using a random uniform distribution within the range defined by food1 and food2 values in city\_land\_uses, which are the minimum and maximum yield values found in literature for each category of urban garden. The function computes a Monte Carlo simulation of 1000 iterations to calculate the confidence interval.

The function that calculates the food production is food\_production. It takes the urban representation (x) as the first argument. If the second argument edible\_df is NULL, the function uses the values from city\_land\_uses as specified above. Otherwise, the user can provide its own values as a data.frame with three columns:

* land\_uses: specifying the category of urban agriculture, it should match the categories from x.
* food1 and food2 specifies the range of the random uniform distribution to randomize yield.

The argument area\_col points to the variable of x that determines the area dedicated to grow plants in each urban garden. If NULL, the total area of each element is used instead. The number passed to interval defines which confidence intervals of the food production must be returned by the function. However, if verbose is set to TRUE, the function returns a vector of length 1,000 with the results of each iteration of the Monte Carlo simulation.

Code snippet 7: Function and arguments to estimate food production

food\_production(  
 x,  
 edible\_df = NULL,  
 area\_col = "edible\_area",  
 interval = 0.95,  
 verbose = FALSE  
)

### Scenarios of urban agriculture

The ediblecity package also provides the user with a function to create new scenarios based on the urban representation and a predefined set of urban agriculture solutions (Table 3) based on where they are located (private gardens, plots on ground or rooftops) and their purpose (private, community or commercial). The function returns a spatial representation of the new scenario (sf object) with the same structure of the urban representation.

Elements created in new scenarios

| Urban agriculture solutions | Location | Purpose |
| --- | --- | --- |
| Edible private garden | Private gardens | Private |
| Community garden | Plots on ground | Community |
| Commercial garden | Plots on ground | Community |
| Rooftop garden | Rooftops | Commercial |
| Hydroponic rooftop | Rooftops | Commercial |

The location of new urban agriculture elements is randomized among all locations that fulfill the requirements of minimum area for that element. However, this is not the case for commercial gardens, they are settled in the larger available locations, assuming that commercial initiatives have the power to acquire the best spots.

The function to create a new scenario is called set\_scenario. It requires many arguments but most of them have default values to facilitate its use. The function needs the urban representation (x). Then three arguments (pGardens, pVacant, pRooftop) control the proportion of new elements that must be created. The next three arguments (edible\_area\_\*) control the proportion of the area of the new elements that is dedicated to grow plants (edible\_area). The edible\_area of each new elements is randomized within the range provided in the arguments. The next trio of arguments (min\_area\_\*) specify the minimal area required to create new elements. If there are not enough elements largen than min\_area\_\* to fulfill the first arguments, a message is displayed to inform the user (unless quiet argument is set to TRUE). Another three arguments (\*\_from) control which elements can be converted from the urban representation to create new urban agriculture solutions. The argument pcommercial controls the percentage of plots on ground and rooftop that should have commercial purposes instead of community. This does not affect private gardens since they are assumed to be for personal use. Finally, area\_field specifies which attribute of x must be used as the area of the elements. By default, it is am attribute called flat\_area that measures the area with an slope lower than 5º (in city\_example).

Code snippet 8: Function and arguments to create new scenarios.

set\_scenario(  
 x,  
 pGardens = 1,  
 pVacant = 1,  
 pRooftop = 1,  
 edible\_area\_garden = c(0.02, 0.3),  
 edible\_area\_vacant = c(0.52, 0.75),  
 edible\_area\_rooftop = c(0.6, 0.62),  
 min\_area\_garden = 10,  
 min\_area\_vacant = 100,  
 min\_area\_rooftop = 100,  
 private\_gardens\_from = "Normal garden",  
 vacant\_from = "Vacant",  
 rooftop\_from = "Rooftop",  
 pCommercial = 0,  
 area\_field = "flat\_area",  
 quiet = FALSE  
)

## Operation

The ediblecity package is compatible with versions of R higher than 2.10. Although, it was created using version 4.2.1. Code snippet 9 shows how to install the last development version, available in github.

Code snippet 9: Code to install the last development version of the package

# install.packages("devtools") # if not yet installed  
devtools::install\_github("icra/ediblecity")

Once the package is installed, it works as any R package. It can be attached to the namespace using library(ediblecity) or preceding the functions with ediblecity::. To check the documentation of the package and its functions, type help(package="ediblecity") in the R console.

## Limitations

As all abstraction of the reality, the equations and algorithms of the ediblecity package present some limitations. One limitation is the use of GIS layers to create scenarios and estimate indicators, which is intrinsically in two dimensions, and sometimes 2.5 dimensions, since we consider the height of buildings. This prevents to consider other urban agriculture solutions that are relevant such as vertical farming. To consider vertical solutions, the ediblecity package should include 3D calculations.

Another limitation is the subset of indicators chosen, this is, as we said, a choice. Other indicators might be chosen instead or added to the current subset. Hopefully, the ediblecity package will be well received by the community of R scientists and other developers will add new indicators to fulfill their own needs. Indeed, this is one of the main advantages of open-source software.

# Use cases

To use the ediblecity package in R, it is necessary to install it first. Code snippet 10 shows how to install the last development version.

Code snippet 10: Code to install the last development version of the package

## Create scenarios of urban agriculture

To our understanding, the most important use case of the ediblecity package is to compare scenarios. To illustrate this, we created two scenarios and compare them with the original city\_example. The package has been designed to work well with the tidyverse framework in R (Wickham et al. 2019), especially, with the map\_\* family in the purrr package (Henry and Wickham 2022a). Therefore, we first create the two scenarios and save them in a list along with the original urban representation, which we called s0 (Code snippet 11). The scenario s1 will convert the 25% of elements to urban agriculture solutions while the scenario s2 will convert the 100%. Half of gardens in vacant plots, streets and rooftop will have commercial purposes.

Since the scenarios and the indicators have some stochastic parameters, the ideal procedure would be to integrate the creation of the scenarios and the estimation of indicators in a Monte Carlo simulation to get the confidence intervals for each combination of scenario and indicator. However, we rather keep things simple to better illustrate how to use the functions provided by the package.

Code snippet 11: Code to create the scenarios.

# Create new scenarios  
scenarios <- map(c(0.25, 1), ~set\_scenario(city\_example,   
 pGardens = .x,  
 pVacant = .x,  
 pRooftop = .x,  
 private\_gardens\_from = "Normal garden",  
 vacant\_from = c("Vacant", "Streets"),  
 rooftop\_from = "Rooftop",  
 pCommercial = 0.5))  
#> Only 442 private gardens out of 453 assumed satisfy the 'min\_area\_garden'  
#> Only 111 vacant plots out of 149 assumed satisfy the 'min\_area\_vacant'  
#> Only 328 rooftops out of 604 assumed satisfy the 'min\_area\_rooftop'  
  
# Add city\_example as s0  
scenarios[[3]] <- city\_example  
  
# Name the scenarios  
names(scenarios) <- c("s1", "s2", "s0")  
scenarios <- scenarios[order(names(scenarios))]

Number of agriculture solutions in each scenario and their surfaces

| land\_use | s0 n | s1 n | s2 n | s0 area | s1 area | s2 area |
| --- | --- | --- | --- | --- | --- | --- |
| Community garden | 1 | 19 | 56 | 320 | 7024 | 14950 |
| Commercial garden | 0 | 19 | 56 | 0 | 28284 | 46769 |
| Edible private garden | 0 | 113 | 442 | 0 | 13599 | 55587 |
| Hydroponic rooftop | 0 | 76 | 164 | 0 | 58360 | 87090 |
| Rooftop garden | 0 | 75 | 164 | 0 | 14217 | 22485 |

## Calculate indicators and compare scenarios

In this section, we calculate the indicators for each scenario and create tables or plots as illustration of how the results can be used.

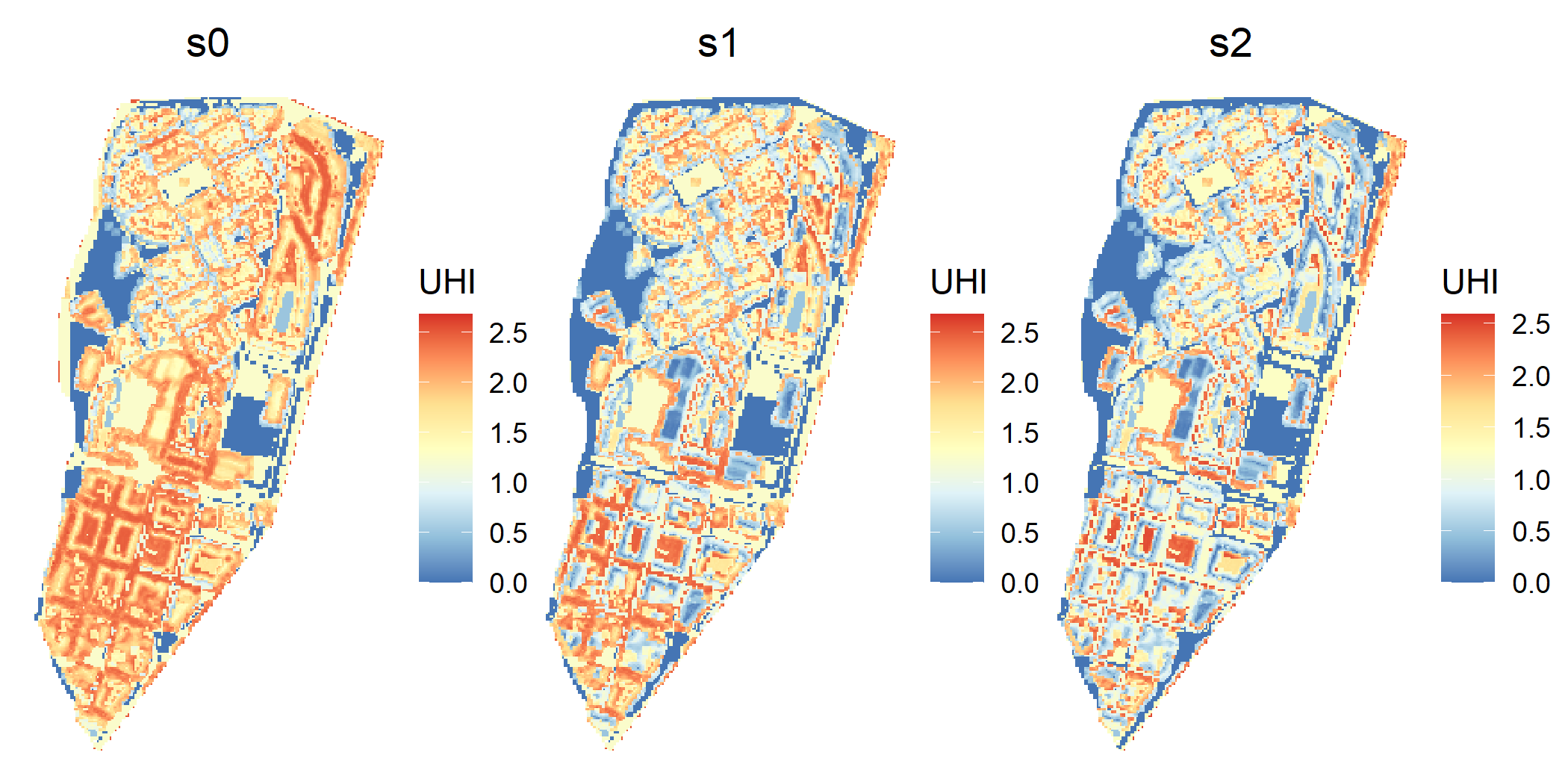
Code snippet 12: Code to create a table with the result of urban heat island in all three scenarios.

# We use the SVF object that is provided for the city\_example in the package  
map\_dfr(scenarios, UHI, SVF = ediblecity::SVF, .id = "Scenario") |>   
 kable(caption = "Summary statistics of urban heat island effect in each scenario (in ºC)")

Summary statistics of urban heat island effect in each scenario (in ºC)

| Scenario | Min. | 1st Qu. | Median | Mean | 3rd Qu. | Max. |
| --- | --- | --- | --- | --- | --- | --- |
| s0 | 0 | 1.25 | 1.60 | 1.49 | 2.1 | 2.7 |
| s1 | 0 | 0.64 | 1.25 | 1.18 | 1.9 | 2.7 |
| s2 | 0 | 0.53 | 0.97 | 0.99 | 1.3 | 2.6 |

As expected the second scenario (s2) has the lowest values for urban heat island, but no too far from the scenario s1. Both present a reduction of approximated 50% in urban heat island regarding the base scenario. We can also generate a raster with the urban heat island for each scenario, like in Figure 2

 Figure 2: Raster returned by the UHI function when return\_raster is set to TRUE.

Code snippet 13: Code to calculate the runoff prevention in each scenario.

map\_dfr(scenarios, runoff\_prev, .id="scenario") |>   
 kable(caption = "Runoff (mm), total rainfall (m^3^) and rainwater harvested in each scenario (m^3^)")

Runoff (mm), total rainfall (m3) and rainwater harvested in each scenario (m3)

| scenario | runoff | rainfall | rainharvest |
| --- | --- | --- | --- |
| s0 | 38 | 108169 | 1188 |
| s1 | 35 | 108169 | 2040 |
| s2 | 35 | 108169 | 1760 |

The total rainfall presented the same value in all scenarios because we use the same rain event and all scenarios represent the same total area. Moreover, although there is an important reduction of runoff and an increase in rainwater harvested regarding the base scenario, there is no improvement from scenario 1 to scenario 2. As shown in Code snippet 13, the rainwater harvested is larger in scenario 1. This is explained because the algorithm uses as catchment areas all adjacent upper areas that are not used for urban agriculture. Hence, as rooftop converted to urban agriculture increases, the availability of catchment areas decrease. The infiltration rates also increase because rooftop gardens retain water but this is not enough to compensate the reduction in harvesting.

Code snippet 14: Code to generate a boxplot of distances to public green areas.

map\_dfc(scenarios, green\_distance, min\_area = 100, verbose = TRUE) |>   
 pivot\_longer(everything()) |>   
 ggplot(aes(x=name, y=as.numeric(value), fill=name))+  
 geom\_boxplot(show.legend = FALSE)+  
 labs(fill="Scenario", x= "Scenario", y="Distance from residences to public green areas")

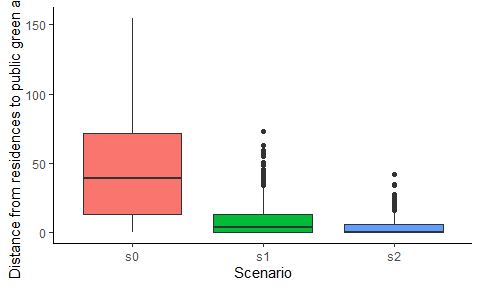


Figure 3: Comparison among scenarios of the distances to each residences to its closest public green area

Code snippet 15: Estimation of NO2 sequestration in all three scenarios

map\_dfr(scenarios, no2\_seq, .id="Scenario") |>   
 kable(caption = "Sequestration of nitrogen dioxide in each scenario")

Sequestration of nitrogen dioxide in each scenario

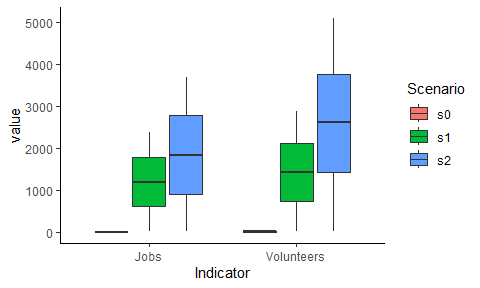
| Scenario | gr/s |
| --- | --- |
| s0 | 102 |
| s1 | 107 |
| s2 | 110 |

Regarding the capacity to absorb NO2, we see a significant improvement from base scenario to scenario 1 but not as larger from scenario 1 to scenario 2.

In the Code snippet 16, there is an example in job to calculate jobs as well as volunteers in the different scenarios.

Code snippet 16: Code to estimate jobs and volunteers in each scenario.

jobs <- scenarios |>   
 map\_dfc(edible\_jobs, verbose = TRUE) |>   
 pivot\_longer(everything(), values\_to = "Jobs")  
  
volunteers <- scenarios |>   
 map\_dfc(edible\_volunteers, verbose = TRUE) |>  
 pivot\_longer(everything(), values\_to = "Volunteers")  
  
bind\_cols(jobs, volunteers["Volunteers"]) |>   
 pivot\_longer(-name, names\_to = "Indicator") |>   
 ggplot(aes(x=Indicator, y=value, fill=name))+  
 geom\_boxplot()+  
 labs(fill="Scenario")

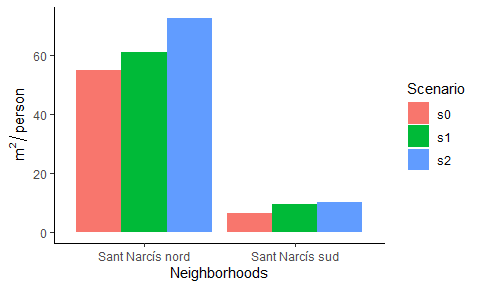
 Figure 4: Comparison of jobs created and volunteers involved in each scenario.

As expected, the base scenario presented very low values, it creates 0 jobs since there is not any commercial garden and a median of 18.1 volunteers, involved in one community garden. The number of jobs and volunteers also increases from scenario 1 to scenario 2 as well as the uncertainty related to the numbers.

Below, we calculate the green per capita in each neighborhoods. To do so, we use another spatial data set provided by the ediblecity package (neighbourhoods\_example) which contains the neighborhoods of city\_example along with the inhabitants in each neighborhood.

Code snippet 17: Code to calculate the green per capita in each neighborhood

scenarios |>   
 map\_dfr(green\_capita,   
 neighbourhoods = neighbourhoods\_example,   
 inh\_col = "inhabitants",  
 name\_col = "name",  
 private = TRUE,  
 verbose = TRUE,  
 .id = "scenarios") |>   
 ggplot(aes(x=name, y=green\_capita, fill=scenarios))+  
 geom\_col(position = position\_dodge())+  
 labs(x="Neighborhoods", y=bquote(m^2/person), fill="Scenario")

 Figure 5: Comparison of green per capita in both neighbourhoods of Sant Narcís.

The difference between both neighborhoods is due to their urban origin. Sant Narcís nord was designed like a city garden while Sant Narcís sud is mainly composed of apartments. The interesting issue is that the improvement across scenarios is larger in Sant Narcís nord that in Sant Narcís sud, evidencing that an increase in urban agriculture is not enough to achieve environmental justice unless it is ideologically planned (Jennings, Johnson Gaither, and Gragg 2012).

The last, but not least, indicator provided by the ediblecity package is the food production. The food production is assumed as higher in gardens for commercial purposes than in community gardens, which the goal is not to maximize the production. This is especially the case of rooftops, since the commercial rooftop gardens are assumed to use hydroponic technology while community rooftop gardens are assumed to use raised beds following the study of Caputo, Rumble, and Schaefer (2020).

Code snippet 18: Code to get confidence intervals of food production in Tm/year.

scenarios |>   
 map\_dfr(food\_production, .id = "Scenario") |>   
 mutate(across(where(is.numeric), ~ .x/1000)) |>   
 kable(caption = "Food production in Tm/year in each scenario")

Food production in Tm/year in each scenario

| Scenario | 5% | 50% | 95% |
| --- | --- | --- | --- |
| s0 | 0.05 | 0.19 | 0.33 |
| s1 | 457.31 | 610.77 | 780.81 |
| s2 | 720.96 | 965.54 | 1215.50 |

Although the median are clearly different, we cannot state that food production is bigger in scenario 2 than in scenario 1 with a 95% of confidence (i.e. p-value > 0.05 in differences between s1 and s2). Taking the most optimistic scenario (s2 at quantile 95%) and considering the value per capita, the urban agriculture in our example could produce 191.94 kg/year/person. The daily intake of fruits and vegetables recommended by FAO is 200 gr/person, i.e. 73 kg/person/year (FAO and WHO 2004). Therefore, our optimistic estimation would provide 2.63 times the neighborhood’s needs in fruits and vegetables. However, it would require (taking also the higher interval) 3510 people working in commercial gardens and 4829 volunteers involved in community gardens, which is 1.32 times the inhabitants of the neighborhood.

# Conclusions

In this paper, we presented the ediblecity package: An R package to to model and estimate the benefits of urban agriculture. The package is ready to be used by R users with a basic level. It can be used to estimate the benefits of real cases as well as to simulate scenarios. In both cases, 8 indicators are calculated. In the example illustrated in this paper, the uncertainty is captured using stochastic parameters. Moreover, the users are able to provide their own ranges in case they have more accurate data for the case study at stake. With more accurate data, the uncertainty can be easily reduced changing the arguments of the functions. Likewise, some assumptions of the models can be override with truly statements.

The ediblecity package is open-source software under MIT license. This allows other R developers to contribute to the package providing new functionalities or improving the existing ones. Therefore, an open-source software is always a work-in-progress.

## Data Avaialability statement

All data underlying the results are available as part of the ediblecity package and no additional source data are required.

## Software availability

* The ediblecity package is available at <https://github.com/icra/ediblecity> under MIT license.
* This paper has been entirely written using RMarkdown, the code to reproduce the paper is available at <https://github.com/icra/ediblecity_paper> under MIT license.

## Authors contributions

JPR, JC and LC contributed to conceptualization, methodology and writing - review & editing. JPR contributed to data curation, formal analysis, software, validation, visualization and writing - original draft preparation. JC and LC contributed to funding acquisition, project administration, resources and supervision.

## Competing interests

No competing interests were disclosed.

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# References

Artmann, Martina, and Katharina Sartison. 2018. “The role of urban agriculture as a nature-based solution: A review for developing a systemic assessment framework.” *Sustainability (Switzerland)* 10 (6): 1937. <https://doi.org/10.3390/su10061937>.

Bache, Stefan Milton, and Hadley Wickham. 2022. *Magrittr: A Forward-Pipe Operator for r*. <https://CRAN.R-project.org/package=magrittr>.

Barthel, Stephan, John Parker, and Henrik Ernstson. 2015. “Food and Green Space in Cities: A Resilience Lens on Gardens and Urban Environmental Movements.” *Urban Studies* 52 (7): 1321–38. <https://doi.org/10.1177/0042098012472744>.

Caputo, S., H. Rumble, and M. Schaefer. 2020. “‘I like to get my hands stuck in the soil’: A pilot study in the acceptance of soil-less methods of cultivation in community gardens.” *Journal of Cleaner Production* 258. <https://doi.org/10.1016/j.jclepro.2020.120585>.

Clinton, Nicholas, Michelle Stuhlmacher, Albie Miles, Nazli Uludere Aragon, Melissa Wagner, Matei Georgescu, Chris Herwig, and Peng Gong. 2018. “A Global Geospatial Ecosystem Services Estimate of Urban Agriculture.” *Earth’s Future* 6 (1): 40–60. <https://doi.org/10.1002/2017EF000536>.

Conrad, O. 2008. “Module Sky View Factor.” SAGA. <http://www.saga-gis.org/saga{\_}tool{\_}doc/2.2.0/ta{\_}lighting{\_}3.html>.

Cronshey, R. G., R. T. Roberts, and N. Miller. 1985. *Urban Hydrology for Small Watersheds (Tr-55 Rev. ).* Edited by USDA Natural Resources Conservation Services. <https://www.nrcs.usda.gov/Internet/FSE{\_}DOCUMENTS/stelprdb1044171.pdf>.

FAO, and WHO. 2004. “Fruit and Vegetables for Health Fruit and Vegetables.” Kobe. <http://www.who.int/dietphysicalactivity/{\%}0Afruit/en/index1.html>.

Farahani, Leila Mahmoudi, Cecily Maller, and Kath Phelan. 2018. “Private Gardens as Urban Greenspaces: Can they compensate for Poor Greenspace Access in lower socioeconomic neighbourhoods?” *Landscape Online* 59: 1–18. <https://doi.org/10.3097/LO.201859>.

Furness, Walter W., and Courtney M. Gallaher. 2018. “Food access, food security and community gardens in Rockford, IL.” *Local Environment* 23 (4): 414–30. <https://doi.org/10.1080/13549839.2018.1426561>.

G’omez-Villarino, María Teresa, and Luis Ruiz-Garcia. 2021. “Adaptive design model for the integration of urban agriculture in the sustainable development of cities. A case study in northern Spain.” *Sustainable Cities and Society* 65 (February): 102595. <https://doi.org/10.1016/J.SCS.2020.102595>.

Gittleman, M., C. J. Q. Farmer, P. Kremer, and T. McPhearson. 2017. “Estimating stormwater runoff for community gardens in New York City.” *Urban Ecosystems* 20 (1): 129–39. <https://doi.org/10.1007/s11252-016-0575-8>.

Grafius, Darren R, Jill L Edmondson, Briony A Norton, Rachel Clark, Meghann Mears, Jonathan L Leake, Ron Corstanje, Jim A Harris, and Philip H Warren. 2020. “Estimating food production in an urban landscape.” *Scientific Reports* 10 (1): 5141. <https://doi.org/10.1038/s41598-020-62126-4>.

Grewal, Sharanbir S., and Parwinder S. Grewal. 2012. “Can cities become self-reliant in food?” *Cities* 29 (1): 1–11. <https://doi.org/10.1016/J.CITIES.2011.06.003>.

Henry, Lionel, and Hadley Wickham. 2022a. *purrr: Functional Programming Tools*. <https://cran.r-project.org/package=purrr>.

———. 2022b. *Rlang: Functions for Base Types and Core r and ’Tidyverse’ Features*. <https://CRAN.R-project.org/package=rlang>.

Hsieh, Yi Hsuan, Jung Te Hsu, and Ting I. Lee. 2017. “Estimating the potential of achieving self-reliance by rooftop gardening in Chiayi City, Taiwan.” *International Journal of Design and Nature and Ecodynamics* 12 (4): 448–57. <https://doi.org/10.2495/DNE-V12-N4-448-457>.

Jennings, Viniece, Cassandra Johnson Gaither, and Richard Schulterbrandt Gragg. 2012. “Promoting environmental justice through urban green space access: A synopsis.” *Environmental Justice* 5 (1): 1–7. <https://doi.org/10.1089/env.2011.0007>.

Kabisch, Nadja, and Dagmar Haase. 2014. “Green justice or just green? Provision of urban green spaces in Berlin, Germany.” *Landscape and Urban Planning* 122 (February): 129–39. <https://doi.org/10.1016/j.landurbplan.2013.11.016>.

Kampa, Marilena, and Elias Castanas. 2008. “Human health effects of air pollution.” *Environmental Pollution* 151 (2): 362–67. <https://doi.org/10.1016/j.envpol.2007.06.012>.

Langemeyer, Johannes, Cristina Madrid-Lopez, Angelica Mendoza Beltran, and Gara Villalba Mendez. 2021a. “Urban agriculture — A necessary pathway towards urban resilience and global sustainability?” *Landscape and Urban Planning* 210: 104055. https://doi.org/<https://doi.org/10.1016/j.landurbplan.2021.104055>.

———. 2021b. “Urban agriculture — A necessary pathway towards urban resilience and global sustainability?” Elsevier B.V. <https://doi.org/10.1016/j.landurbplan.2021.104055>.

Lin, Brenda B., S. M. Philpott, and S. Jha. 2015. “The future of urban agriculture and biodiversity-ecosystem services: Challenges and next steps.” *Basic and Applied Ecology* 16 (3): 189–201. <https://doi.org/10.1016/j.baae.2015.01.005>.

Lupia, Flavio, Valerio Baiocchi, Keti Lelo, and Giuseppe Pulighe. 2017. “Exploring Rooftop Rainwater Harvesting Potential for Food Production in Urban Areas.” *Agriculture 2017, Vol. 7, Page 46* 7 (6): 46. <https://doi.org/10.3390/AGRICULTURE7060046>.

MacRae, Rod, Eric Gallant, Sima Patel, Marc Michalak, Martin Bunch, and Stephanie Schaffner. 2010. “Could Toronto provide 10% of its fresh vegetable requirements from within its own boundaries? Matching consumption requirements with growing spaces.” *Journal of Agriculture, Food Systems, and Community Development* 1 (2): 105–27. <https://doi.org/10.5304/jafscd.2010.012.008>.

Mayer, Helmut. 1999. “Air pollution in cities.” *Atmospheric Environment* 33 (24-25): 4029–37. <https://doi.org/10.1016/S1352-2310(99)00144-2>.

Pebesma, Edzer. 2018a. “Simple Features for R: Standardized Support for Spatial Vector Data.” *The R Journal* 10 (1): 439–46. <https://doi.org/10.32614/RJ-2018-009>.

———. 2018b. “Simple Features for R: Standardized Support for Spatial Vector Data.” *The R Journal* 10 (1): 439–46. <https://doi.org/10.32614/RJ-2018-009>.

———. 2021. *stars: Spatiotemporal Arrays, Raster and Vector Data Cubes*. <https://cran.r-project.org/package=stars>.

———. 2022. *Stars: Spatiotemporal Arrays, Raster and Vector Data Cubes*. <https://CRAN.R-project.org/package=stars>.

R Core Team. 2022. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. <https://www.R-project.org/>.

Richardson, Jeffrey J., and L. Monika Moskal. 2016. “Urban food crop production capacity and competition with the urban forest.” *Urban Forestry & Urban Greening* 15 (January): 58–64. <https://doi.org/10.1016/J.UFUG.2015.10.006>.

Säumel, Ina, Suhana E. Reddy, and Thomas Wachtel. 2019. “Edible city solutions-one step further to foster social resilience through enhanced socio-cultural ecosystem services in cities.” *Sustainability (Switzerland)* 11 (4). <https://doi.org/10.3390/su11040972>.

Shukla, P. R., J. Skea, E. Calvo Buendia, V. Masson-Delmotte, H.-O. Pörtner, D. C. Roberts, P. Zhai, et al. 2019. “IPCC, 2019: Climate Change and Land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems.” IPCC. <https://www.ipcc.ch/report/ar6/wg1/downloads/report/IPCC{\_}AR6{\_}WGI{\_}Full{\_}Report.pdf>.

Soga, Masashi, Daniel T. C. Cox, Yuichi Yamaura, Kevin J. Gaston, Kiyo Kurisu, and Keisuke Hanaki. 2017. “Health benefits of urban allotment gardening: Improved physical and psychological well-being and social integration.” *International Journal of Environmental Research and Public Health* 14 (1). <https://doi.org/10.3390/ijerph14010071>.

Steel, C. 2008. *Hungry city: how food shapes our lives*. London: Chatto & Windus.

Theeuwes, Natalie E., Gert Jan Steeneveld, Reinder J. Ronda, and Albert A. M. Holtslag. 2017. “A diagnostic equation for the daily maximum urban heat island effect for cities in northwestern Europe.” *International Journal of Climatology* 37 (1): 443–54. <https://doi.org/10.1002/joc.4717>.

Tornaghi, Chiara. 2012. “Public space, urban agriculture and the grassroots creation of new commons: lessons and challenges for policy makers.” In *Sustainable Food Planning: Evolving Theory and Practice*, edited by A. Viljoen and J. S. C. Wiskerke, 349–64. Wageningen Academic Publishers. <https://doi.org/10.3920/978-90-8686-187-3_29>.

Wickham, Hadley, Mara Averick, Jennifer Bryan, Winston Chang, Lucy D’Agostino McGowan, Romain François, Garrett Grolemund, et al. 2019. “Welcome to the {tidyverse}.” *Journal of Open Source Software* 4 (43): 1686. <https://doi.org/10.21105/joss.01686>.

Wickham, Hadley, and Jennifer Bryan. 2022. *R Packages (2e)*. O’REILLY. <https://r-pkgs.org/>.

Wickham, Hadley, Peter Danenberg, Gábor Csárdi, and Manuel Eugster. 2022. *Roxygen2: In-Line Documentation for r*. <https://CRAN.R-project.org/package=roxygen2>.

Wickham, Hadley, Romain François, Lionel Henry, and Kirill Müller. 2022. *Dplyr: A Grammar of Data Manipulation*. <https://CRAN.R-project.org/package=dplyr>.

Wickham, Hadley, Jim Hester, Winston Chang, and Jennifer Bryan. 2022. *Devtools: Tools to Make Developing r Packages Easier*. <https://CRAN.R-project.org/package=devtools>.