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| ediblecity: an R package to model and estimate the benefits of urban agriculture **[version 1; peer review: 3 approved with reservations]** | |
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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, NO 2 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 generate 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. |
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## Introduction

Urban agriculture is becoming one of the pillars of the urban ecological transition ( [Säumel](#ref-34) *[et al.,](#ref-34)* [2019](#ref-34)). Likewise, urban agriculture might have a key role ensuring food security in an urbanized planet ( [Barthel](#ref-3) *[et al.,](#ref-3)* [2015](#ref-3)). As a consequence, some research has paid attention on the actual or potential food production of urban agriculture ( [Grafius](#ref-14) *[et al](#ref-14)*[., 2020](#ref-14); [Richardson & Moskal, 2016](#ref-33)). However, some others authors argued that the importance of urban agriculture does not reside in its ability to produce food but in the social benefits it provides, such as public health ( [Soga](#ref-36) *[et al](#ref-36)*[., 2017](#ref-36)) and social cohesion ( [Säumel](#ref-34) *[et al.,](#ref-34)* [2019](#ref-34)). Moreover, other authors stated that urban agriculture can provide environmental benefits as well, such as climate regulation ( [Clinton](#ref-5) *[et al](#ref-5)*[., 2018](#ref-5)) or water runoff prevention ( [Gittleman](#ref-13) *[et al](#ref-13)*[., 2017](#ref-13)).

However, there is a lack of systematic quantification of the benefits provided by urban agriculture ( [Langemeyer](#ref-22) *[et al](#ref-22)*[., 2021a](#ref-22)). For instance, there is no clear evidence to what extent urban agriculture could contribute to reduce the urban heat island ( [Lin](#ref-24) *[et al.,](#ref-24)* [2015](#ref-24)) or to a greener economy ( [Säumel](#ref-34) *[et al.,](#ref-34)* [2019](#ref-34)). However, most studies have been focused on a single initiative and one benefit ( [Artmann & Sartison, 2018](#ref-1)).

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 have provided some insights that can guide the implementation of urban agriculture. For instance, some models explore the rainwater harvesting potential of urban agriculture ( [Gittleman](#ref-13) *[et al](#ref-13)*[., 2017](#ref-13); [Lupia](#ref-25) *[et al](#ref-25)*[., 2017](#ref-25)). Broader, [Gómez-Villarino and Ruiz-Garcia (2021)](#ref-12) 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](#ref-14) *[et al](#ref-14)*[., 2020](#ref-14); [Grewal & Grewal, 2012](#ref-15); [Hsieh](#ref-18) *[et al.,](#ref-18)* [2017](#ref-18); [MacRae](#ref-26) *[et al](#ref-26)*[., 2010](#ref-26)). 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 to a neighborhood of Girona (Spain).

While the package offers default values for nearly all necessary parameters, it's worth noting that these defaults have been tailored to our specific example, which focuses on a mid-sized Western Mediterranean European city. Nevertheless, it's important to emphasize that users have the flexibility to customize all parameters according to their specific context.

## 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](#ref-32)), 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](#ref-32)) in RStudio desktop v. 2022.07.02. The package structure was assisted by the package devtools ( [Wickham](#ref-44) *[et al](#ref-44)*[., 2022d](#ref-44)) following the principles in [Wickham and Bryan (2022a)](#ref-41). Likewise, the documentation of the functions was assisted by the package roxygen2 ( [Wickham](#ref-42) *[et al](#ref-42)*[., 2022b](#ref-42)). The dependencies of the package are:

* dplyr (>= 1.0.6) ( [Wickham](#ref-43) *[et al](#ref-43)*[., 2022c](#ref-43))
* magrittr (>= 2.0.1) ( [Bache & Wickham, 2022](#ref-2))
* sf (>=0.9) ( [Pebesma, 2018a](#ref-28))
* stars (>= 0.5) ( [Pebesma, 2022](#ref-31))
* rlang (>= 1.0) ( [Henry & Wickham, 2022b](#ref-17))

***Urban representation of the city of interest.*** The ediblecity package provides eight functions to estimate eight 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. This 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](#f1)). This example can help the users to create the representation of their cities of interest. In the [Table 1](#T1) 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](#ref-29))

### Figure 1. The urban representation included in the ‘ediblecity‘ package as example.

### Table 1. 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 < 5⍛) |
| 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 default attributes of each green typology in the urban representation used to estimate the indicators ( [Table 2](#T2)). This includes types of urban agriculture along with other types of green infrastructure. 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](#T2), they are logical variables ( *i.e.* TRUE/FALSE) used internally by the package to select urban agriculture elements.

### Table 2. 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 |

pGreen is the proportion of green of the urban element. In urban agriculture solutions, this is overridden by the attribute edible\_area. The following attributes come in pairs (min, max) 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. We used a random uniform distribution, i.e., all values within the rage have the same probability of being picked. no2\_seq is the capacity of the element to capture NO 2 in gr/s. food is the food productivity in kg/m 2 and CN is their curve number, used to calculate infiltration rates. The details are provided in following sections.

***Indicators estimated.***

The current version of the package includes 8 indicators related to various urban challenges defined, as defined in part by a handbook of indicators to evaluate the impact of nature-based solutions (Dumitru & Wendling, 2021) From this source, we chose 8 indicators that meet the following criteria: (1) Measurability: The indicators can be quantitatively measured based on the area or location. (2) Direct Influence: Urban agriculture (UA) has a direct impact on the indicators, meaning that changes in UA will affect the indicator's values. (3) Relevance to UC: The indicators are directly linked to a specific UC, and at least indirectly connected to another UC, allowing us to capture multiple dimensions of urban sustainability. By considering these criteria, we ensured that the selected indicators provide a holistic understanding of the impact of UA on urban challenges.

It's worth noting that the tool is open source. Therefore, new indicators can be added in the future either by the creators or by other users interested in specific aspects of UA.

**Urban heat island** The urban heat island is a measure of how urban agriculture can contribute to climate change adaptation, specifically to adapt cities to the increasing heat waves ( [Langemeyer](#ref-23) *[et al](#ref-23)*[., 2021b](#ref-23)). The indicator uses the equation developed by [Theeuwes](#ref-38) *[et al](#ref-38)*[. (2017)](#ref-38), 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](#ref-7)).

UHI=1N∑i=1N(2−SVFi−Fvegi)×QqlCair×Pair×ΔT3U4

where *Fveg* is the proportion of vegetation in cell *i*; *Q ql* is the daily average global radiation (in W/m 2/hour); *C air* is the air heat capacity (in J); *P air* is air density (in kg/m 3); ∆ *T* is the difference between the maximum and minimum daily average temperatures (in ⍛C); and *U* 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 (code snippet 1). 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 land\_use in the urban representation ( *Fveg* in the equation). 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](#ref-30)) 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,

*# Urban representation*

SVF,

*# Raster with the sky view factor*

green\_df =

NULL,

*# Fveg in the UHI equation*

Qql =

6.11,

*# Daily average global radiation*

Cair =

1007,

*# Air heat capacity*

Pair =

1.14,

*# Air density*

Tmax =

30.8,

*# Maximum daily average temperature*

Tmin =

20,

*# Minimum daily average temperature*

windspeed =

2.77,

*# Average wind speed*

return\_raster =

FALSE,

*# Should function return a raster or numeric values?*

verbose =

FALSE

*# Should the function return all the values or a summary?*

)

**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](#ref-35) *[et al](#ref-35)*[., 2019](#ref-35)). 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](#ref-8) *[et al.,](#ref-8)* [1985](#ref-8)).

Q=(P−Ia)2(P−Ia)+S

where *Q* is the runoff in *mm*; *P* is the rainfall volume in mm; *I a* is the initial abstraction (all losses before runoff begins); and *S* is the potential soil moisture retention, which is a function of the curve number (which is determined by hydrologic soil group, see [Cronshey, Roberts, and Miller (1985)](#ref-8) for more details on the method). The SCS generalizes *I a* as 0 *.*2 *S*, we modified this generalization to include the rainwater harvested:

Ia=0.2S+∑i=1Nmin{Rh,Ws}i

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

The runoff\_prev function estimates the runoff ( *Q* in the equation) as well as the total rainfall in x and the total rainwater harvested in cubic meters (code snippet 2). Along with the urban representation (x), the user must provide a data.frame ( runoff\_df argument) with four variables: land use, minimum and maximum curve numbers and a logical variable indicating whether the land use (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 (in m) 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, proportional to the surface of the element (in l/m 2). The volume of each tank in the city is randomized within this range and multiplied by the element where they are located. All randomizations follow a random uniform distribution within the correspondent range.

Code snippet 2: Function and arguments to estimate runoff prevention

runoff\_prev(

x,

*# Urban representation*

runoff\_df =

NULL,

*# A data.frame with land use values*

rain =

85,

*# Rain event in mm.*

floors\_field = "floors",

*# Variable in `x` containing the number of floors of each element*

harvest\_dist =

10

,

*# Maximum distance to consider for rainwater harvesting surfaces*

tank\_size =

c(

0

,

45

)

*# Range for the size of tanks in m3*

)

**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 (code snippet 3). 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 the ones contained by the variable passed to 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 from residences to green areas (larger than min\_area) is returned.

Code snippet 3: Function and arguments to calculate green accessibility

green\_distance(

x,

*# The urban representation*

green\_cat =

NULL,

*# The land uses considered urban green*

residence\_col =

"land\_use\_verbose"

,

*# The variable than contains information of what is a residence*

residences =

"Residence"

,

*# The categories of former variable considered residences*

min\_area =

5000

,

*# Smaller areas are not included in the calculations*

percent\_out =

FALSE,

*# Should the function return a percentage of residences out*

max\_dist =

300

,

*# Which is the distaince to consider that a residence is out?*

verbose =

FALSE

*# Should return a summary of distance or all values?*

)

**Nitrogen dioxide sequestration** Nitrogen dioxide is a good proxy of overall air quality ( [Mayer, 1999](#ref-27)) and one of the most concerning issues in cities, with important consequences on respiratory diseases and lung cancer ( [Kampa & Castanas, 2008](#ref-21)). This indicator calculates the amount of NO 2 sequestered by urban green and urban agriculture solutions (in g/s).

NO2seq=∑i=1Nai×capi1000

where *a i* is the area (in m 2) of the element *i*; and *cap i* is the capacity of element *i* to sequester NO 2 (in *µ*g·s -1m -2).

The function to estimate the NO 2 sequestered is no2\_seq (code snippet 4). It has only two arguments; the urban representation ( x) and a data.frame with four columns:

* land\_uses: Column with the land use.
* no2\_seq1: The low range of NO2 sequestration of each function (in *µ*g·s -1m -2).
* no2\_seq2: The high range of NO2 sequestration of each function (in *µ*g·s -1m -2).
* pGreen: The proportion of green surface in each function.

When the argument is NULL (default), the function uses the city\_land\_uses dataset provided with the package that contains NO 2 sequester capacity of different types of urban green.

The capacity ( *cap i* 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 NO 2 sequestration

no2\_seq(x,

*# The urban representation*

green\_df =

NULL)

*# The data.frame with the NO2 sequestration capacity of each land use.*

**Jobs created and volunteers involved** 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. Therefore, 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 spent by new workers (jobs created). Both indicators use the same equation:

jobs|volunteers=∑i=1Nai×k

where *a i* is the area in m 2 used to grow plants ( edible\_area) in the element *i*; and *k* is the number of jobs or volunteers by m 2. In both functions, *k* 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 default values were based on two sources, an empirical study ( [CoDyre](#ref-6) *[et al.,](#ref-6)* [2015](#ref-6)) and the FoodMetres project.

The functions to calculate these indicators are edible\_jobs and edible\_volunteers respectively (code snippet 5). They share the same arguments, expect for jobs and volunteers, which is the value of *k* in the previous equation. As usual, the first argument is the urban representation ( x), edible is the land uses in x that are urban agriculture solutions (if NULL, city\_land\_uses is used as default), the attribute of x defining the area used to grow plants is area\_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,

*# The urban representation*

jobs =

c(

0.000163,

0.022

),

*# The k parameter*

edible =

NULL

,

*# The land uses that are urban agriculture*

area\_col =

"edible\_area"

,

*# The variable containing the surface dedicated to grow plants*

interval =

0.95

,

*# The confidence interval returned by the function*

verbose =

FALSE

*# Should return all values or a summary?*

)

edible\_volunteers(

x,

*# The urban representation*

volunteers =

c(

0.00163,

0.22

),

*# The k parameter*

edible =

NULL

,

*# The land uses that are urban agriculture*

area\_col =

"edible\_area"

,

*# The variable containing the surface dedicated to grow plants*

interval =

0.95

,

*# The confidence interval returned by the function*

verbose =

FALSE

*# Should return all values or a summary?*

)

**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 & Haase, 2014](#ref-20)). At the neighborhood level a ratio between the most and least green neighborhoods is calculated, with higher values meaning a major difference between neighborhoods and less spatial justice. Moreover, since wealthier areas tend to have more private gardens ( [Farahani](#ref-10) *[et al.,](#ref-10)* [2018](#ref-10)), these can be included in the account of green per capita to not underestimate green per capita in those neighborhoods.

The function to calculate this indicator is green\_capita (code snippet 6). 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. At a city level, the function returns the average amount of green per capita in the city (in m 2/inhabitant). Likewise there are two options to calculate green per capita at a neighbourhood level. The urban representation can contain two variables indicating the name of the neighbourhood 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,

*# The urban representation*

green\_categories =

NULL,

*# The categories considered as urban green*

inhabitants =

NULL,

*# The number of inhabitants in the city*

neighbourhoods =

NULL,

*# The spatial representation of neighborhoods*

name\_col =

NULL,

*# The variable that contains de name of the neighborhoods*

inh\_col =

NULL,

*# The variable that contains the inhabitants of the neighborhoods*

private =

FALSE,

*# Should private green be considered?*

verbose =

FALSE,

*# Should return all the information or just the ratio?*

min\_inh =

0

*# Neighborhoods with less hanbitants are excluded*

)

**Food production** Although many authors stated that the main goal of urban agriculture is not to produce food ( [Säumel](#ref-34) *[et al.,](#ref-34)* [2019](#ref-34); [Tornaghi, 2012](#ref-39)), food production is undoubtedly an important component of urban gardens ( [Furness & Gallaher, 2018](#ref-11); [Steel, 2008](#ref-37)) and the most frequent output modeled at a city scale ( [Grafius](#ref-14) *[et al](#ref-14)*[., 2020](#ref-14); [Grewal & Grewal, 2012](#ref-15)). The food production is measured in terms of productivity (kg/m 2):

Foodproduction=∑i=1Nykai

where *y k* is the yield (in *kg/m* 2) of the category *k* of urban garden; and *a i* is the area of urban garden *i* in *m* 2. By default, the value of *y* 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 the literature for each category of urban garden. The function computes a Monte Carlo simulation of 1,000 iterations to calculate the confidence interval.

The function that calculates the food production is food\_production (code snippet 7). 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 interval 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,

*# The urban representation*

edible\_df =

NULL,

*# Dataframe containing information on yields*

area\_col =

"edible\_area",

*# Variable of x with surface*

interval =

0.95,

*# Confidence interval returned by the function*

verbose =

FALSE

*# Should return all the values or just the confidence interval?*

)

***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](#T3)) 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.

### Table 3. 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 (code snippet 8). 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 larger 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 5⍛ (in city\_example).

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

set\_scenario(

x,

*# The urban representation*

pGardens =

1

,

*# Proportion of private edible gardens*

pVacant =

1

,

*# Proportion of vacant plots converted to gardens on ground*

pRooftop =

1

,

*# Proportion of rooftops converted to rooftop gardens*

edible\_area\_garden =

c(

0.02

,

0.3

),

*# Proportion of surface dedicated to grow plants in private gardens*

edible\_area\_vacant =

c(

0.52

,

0.75

),

*# And in gardens on ground*

edible\_area\_rooftop =

c(

0.6

,

0.62

),

*# And in rooftop gardens*

min\_area\_garden =

10

,

*# Exclude smaller private gardens*

min\_area\_vacant =

100

,

*# Exclude smaller vacant plots*

min\_area\_rooftop =

100

,

*# Exclude smaller rooftops*

private\_gardens\_from =

"Normal garden"

,

*# Land uses to be converted to private edible gardens*

vacant\_from =

"Vacant"

,

*# Land uses to be converted to gardens on ground*

rooftop\_from =

"Rooftop"

,

*# Land uses to be converted to rooftop gardens*

pCommercial =

0

,

*# Proportion of commercial gardens vs community gardens*

area\_field =

"flat\_area"

,

*# Variable of x containing available surface in each element*

quiet =

FALSE

*# Should the function raise warnings?*

)

### Operation

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

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

*# install.packages("devtools") # if not yet installed*

install.packages(

"ediblecity",

repos =

"jospueyo.r-universe.dev")

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 abstractions of 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 from considering 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.

Likewise, we opted to only choose indicators to estimate the benefits of urban agriculture. However, urban agriculture has also some drawbacks that could be measured. Certainly, various research studies have drawn attention to a range of concerns within the realm of urban agriculture (UA). For instance, Graefe et al. (2019) emphasized the issue of heavy metal presence in cultivated plants, while Perrin et al. (2015) discussed the improper use of pesticides and fertilizers. These factors not only pose threats to both the environment and human well-being but also bring into focus the need for sustainable practices. In a similar vein, (Whittinghill et al., 2016) shed light on the dual nature of rooftop gardens. While they are effective in mitigating runoff, they can also contribute to nutrient runoff, especially when compared to extensive green roofs. This has implications for the quality of runoff water, underscoring the complexity of UA's environmental impacts. Moreover, beyond the potential environmental and health consequences, UA can also give rise to adverse social effects, as highlighted by Hawes et al. (2022). These repercussions, like the phenomenon of green gentrification, deserve careful consideration in the context of urban agriculture development.

## Use cases

To replicate this section, apart from the ediblecity package, you will need to load the following packages in your R namespace using the function library(<package>):

* dplyr (1.1.2) (Wickham, François, et al., 2023)
* ggplot2 (3.4.2) (Wickham, 2016)
* knitr (1.42) (Xie, 2023)
* purr (1.0.1) (Wickham & Henry, 2023)
* tidyr (1.3.0) (Wickham, Vaughan, et al., 2023)

### 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 compared them with the original city\_example ( [Table 4](#T4)). The package has been designed to work well with the tidyverse framework in R ( [Wickham](#ref-40) *[et al](#ref-40)*[., 2019](#ref-40)), especially, with the map\_\* family in the purrr package ( [Henry & Wickham, 2022a](#ref-16)). 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 10). 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.

### Table 4. Number of agriculture solutions in each scenario and their surfaces (in squared meters).

| **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 |

Code snippet 10: 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))]

### 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 11: 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)"

)

As expected the second scenario (s2) has the lowest values for urban heat island, but not too far from the scenario s1 ( [Table 5](#T5)). Both present a reduction of approximated 50% in average urban heat island regarding the base scenario. The absolute reduction in degrees can also be compared to the average temperature in summer in the study area. In our case study, July 2022 had an average temperature of 28ºC. The reduction caused by UA would suppose a reduction of 3.5%. We can also generate a raster with the urban heat island for each scenario, like in [Figure 2](#f2)

### Table 5. Summary statistics of urban heat island effect in each scenario (in ⍛C).

| **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 |

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

Code snippet 12: Code to calculate the runoff prevention in each scenario.

map\_dfr(scenarios, runoff\_prev,

.id=

"scenario"

) |>

kable(

caption =

"Runoff (mm), total rainfall (mˆ3ˆ) and rainwater harvested in each scenario (mˆ3ˆ)"

)

The total rainfall presented the same value in all scenarios because we used the same rain event and all scenarios represent the same total area ( [Table 6](#T6)). Moreover, although there was an important reduction of runoff and an increase in rainwater harvested regarding the base scenario, there was no improvement from scenario 1 to scenario 2. As shown in Code snippet 12, the rainwater harvested was 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. However, harvested water has also some benefits, mainly water reuse. For instance, Girona’s inhabitants have an average consumption of 134 litres /day. This multiplied by the inhabitants of Sant Narcís gives a total consumption of 847 m3/day. Hence, the water harvested in scenario 1 could provide all the water in the neighbourhood during 2 days and a half.

### Table 6. Runoff (mm), total rainfall (m 3) and rainwater harvested in each scenario (m 3).

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

Code snippet 13: Code to generate a boxplot of distances to public green areas (result show in [Figure 3](#f3)).

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

\n

to public green areas (m)"

)

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

This indicator can be used to explore the fullfilment of WHO recommendations, which recommend that all citizens should have a green area larger than 0,5 ha closer than 300 metres (WHO, 2017). This can be achieved by adjusting the argument min\_area used to calculate the indicator that filters all the green areas smaller than the value provided to the argument.

Code snippet 14: Estimation of NO 2 sequestration in all three scenarios

map\_dfr(scenarios, no2\_seq,

.id=

"Scenario"

) |>

kable(

caption =

"Sequestration of nitrogen dioxide in each scenario"

)

Regarding the capacity to absorb NO 2, we see a significant improvement from base scenario to scenario 1 but not as larger from scenario 1 to scenario 2 ( [Table 7](#T7)). Considering the car emissions limitation imposed by the Euro 6 standard and assuming that cars drive at 50 km/h in the city, The sequestration of scenario 2 is approximately equivalent to neutralizing emissions from 130 cars (1.04 gr/s/car).

### Table 7. Sequestration of nitrogen dioxide in each scenario.

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

In the Code snippet 15, there is an example to calculate jobs as well as volunteers in the different scenarios.

Code snippet 15: 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(

y =

"People"

,

fill=

"Scenario"

)

As expected, the base scenario presented very low values; it created 0 jobs since there were no commercial garden and a median of 18.1 volunteers involved in one community garden. The number of jobs and volunteers also increased from scenario 1 to scenario 2 as well as the uncertainty related to the numbers ( [Figure 4](#f4)). The number of jobs and volunteers can be compared to the population in the neighbourhood. In that case, using median values, the jobs of scenario 2 represents 30% of the population while the volunteers the 40%. We must note, that the scenario 2 is converting all the available streets and rooftops to urban gardens, and so the number may feel a bit overestimated.

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

Below, we calculated the green per capita in each neighborhoods (code snippet 16). 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 16: 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(),

color =

"black"

)+

labs(

x=

"Neighborhoods"

,

y=

bquote(mˆ

2

/person),

fill=

"Scenario"

)

The difference between both neighborhoods ( [Figure 5](#f5)) 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](#ref-19) *[et al.,](#ref-19)* [2012](#ref-19)). However, remarkably, Sant Narcís sud increased from 6.6 to 9.4 m2/capita from base scenario to scenario 1, surpassing the standard of 9 m2/capita.

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

The last, but not least, indicator provided by the ediblecity package is the food production. The food production is assumed to be higher in gardens for commercial purposes than in community gardens, the goal of which is not to maximize the production. This is especially the case of rooftops, since 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)](#ref-4).

Code snippet 17: 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"

)

Although the medians 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) ( [Table 8](#T8)). 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 the FAO is 200 gr/person, *i.e.* 73 kg/person/year ( [FAO & WHO, 2004](#ref-9)). 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) 3,510 people working in commercial gardens and 4,829 volunteers involved in community gardens, which is 1.32 times the inhabitants of the neighborhood.

### Table 8. 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 |

### Disclaimer

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 kept things simple to better illustrate how to use the functions provided by the package.

## Conclusions

In this paper, we presented the ediblecity package: An R package 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 by changing the arguments of the functions. Likewise, some assumptions of the models can be overridden 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 availability

### Underlying data

Zenodo: icra/ediblecity: To zenodo, [https://doi.org/10.5281/zenodo.7913285](https://doi.org/10.5281/zenodo.7913285" \t "xrefwindow)

Data are available under the terms of the Creative [Commons Attribution 4.0 International license](https://creativecommons.org/licenses/by/4.0/" \t "xrefwindow) (CC-BY 4.0).

## Software availability

* The ediblecity package is available from [https://github.com/icra/ediblecity](https://github.com/icra/ediblecity" \t "xrefwindow)

Archived code at time of publication: [https://doi.org/10.5281/zenodo.7913285](https://doi.org/10.5281/zenodo.7913285" \t "xrefwindow)

License: [MIT license](https://opensource.org/license/mit/" \t "xrefwindow)

* This paper has been entirely written using RMarkdown, the code to reproduce the paper is available at [https://github.com/icra/ediblecity\_paper](https://github.com/icra/ediblecity_paper" \t "xrefwindow) 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.

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|  |  |
| --- | --- |
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