XXXVI CONFERENZA ITALIANA DI SCIENZE REGIONALI

MULTI-SOURCE SPATIAL DATA FOR A BETTER MANAGEMENT OF RAINWATER AND URBAN CULTIVATED AREAS: A CASE STUDY IN ROME, ITALY

Flavio LUPIA[1], Francesca GIARÈ[2], Valerio BAIOCCHI[3], Keti LELO[4]

ABSTRACT

In the last decade citizens interest toward local food production, food sustainability and environmental stewardship has grown exponentially and urban agriculture (UA) is nowadays one of the answer to this new collective awareness. The analysis of the spatial dimension of UA in metropolitan areas is the starting point for investigating its characteristics, the positive impacts on the urban environment and, in general, for a better planning and management of green and vacant spaces. This contribution explores the spatial distribution of residential cultivated parcels in the urban area of Rome and their sustainability in terms of water required for irrigation. In particular, the water required for growing crops during the summer season (April-September) was estimated by using data on land use and parcels size. Later, the share of irrigation that might be provided from the rainwater harvestable from roofs nearby parcels was computed by using the monthly rain average for the period 1950-2010 and the roofs size. Data on cultivated residential areas in 2013 were created by photointerpretation of the very high resolution imagery provided by Google Earth. Updated roofs polygons were not available on official maps, so an automated objected oriented classification on WorldView2 high resolution imagery was used. The method proposed provide a preliminary assessment of one of the component of urban water use that might be useful to support sustainable urban water management actions.

[1] CREA - Consiglio per la Ricerca in Agricoltura e l'Analisi dell'Economia Agraria, via Nomentana 41, 00161, Roma, e-mail: lupia@inea.it. (corresponding author)
[2] CREA - Consiglio per la Ricerca in Agricoltura e l'Analisi dell'Economia Agraria, via Nomentana 41, 00161, Roma, e-mail: giare@inea.it.
[3] DICEA - Sapienza Università di Roma, Via Eudossiana, 18 Roma, e-mail: valerio.baiocchi@uniroma1.it.
[4] Centro di ateneo per lo studio di Roma (CROMA), Università degli studi Roma Tre, Via Ostiense 139, Roma, e-mail: keti.lelo@uniroma3.it.

1. Introduction

Urban agriculture (UA) can simply be defined as the cultivation of crops in the urban areas taking on different forms and meanings. UA is a livelihood activity for low-income groups (e.g. in the Global South), it can be a mean for additional income for middle-income households, while for high-income households (e.g. in the Global North) it features as the tool for ensuring a more environmentally friendly form of food production (Stewart et al., 2013). The urban food production increases green spaces in cities (vacant land and abandoned sites are often used), and enhances biodiversity. UA is intertwined with concepts such as urban food security, nutrition (De Zeeuw et al., 2011), resilience (Barthel and Isendahl, 2013), sustainability (Specht et al., 2013) and environment, but also with ideas of beautification, leisure and exercise, and social interaction. UA also provides ecosystem services at different scales within urban areas (McDonald, 2009): at local scale (e.g. temperature regulation, water and pollutant filtration), landscape scale (climate mitigation, pollination) and global scale (carbon mitigation, biodiversity).

UA and green spaces requires water for their maintenance competing with the other urban water uses. In the Mediterranean countries the competition can be exacerbated especially during the summer months and the situation will be worsened in the future due to Climate Change, increasing urbanization and population growth. While, at the same time, since cities are made up mainly by extended sealed surfaces (e.g. streets, roofs and car parks), the risks of floods and landslides due to difficulties in the storm water management are becoming more and more frequent.

Agricultural activities in cities can indirectly improve urban water management, in fact green and cultivated spaces allow rainwater and runoff to drain through the soil and the need for costly storm water sewers and drainage can be minimised. To invest in urban agriculture, therefore, is just as necessary as developing a network of channels and drains (Deelstra et al., 2000). However, agriculture should be performed with a sustainable irrigation management by understanding the crops water requirements to lessen environmental risks and increasing water use efficiency. Analysing the potential of new sources for irrigation, such as rainwater harvestable from roofs, can contribute to the development of more productive agricultural activities by reducing the resort to other irrigation sources such as the costly water from aqueduct, wells or, in the worst case, from river or canals that might be heavily contaminated in urban areas (Mancini et al., 2005). Assessing crop water requirements and availability of rainwater at urban level is useful to drive proper planning choices.

This study provide a first estimation of irrigation water requirement of residential gardens (RGs) with fruit and vegetables located in the urban area of the city of Rome that is one of component to consider in the urban water management (Lupia and Pulighe, 2015). In detail, we aim to address the following questions:

- Which is the total amount of water required to irrigate the crops cultivated in the RGs located in the urban area?
- How much rainwater could be harvested from the building roof located nearby each RGs?
- Which is the degree of self-sufficiency in irrigation of RGs by comparing the irrigation requirements and the total annual rainwater harvestable from roofs.

Providing answers to these questions is often challenging since the required high resolution spatial data are not available or not accessible, as in the case of Rome (Italy). The lack of spatial data with adequate resolution could be obviated by exploiting datasets created with different methods and sources: photointerpretation of Google Earth imagery for the creation of the RGs dataset and automatic image processing of very high resolution satellite imagery for the extraction of the roof data.

2. Study area and data

2.1 Study area

The study area is located in the city of Rome, the most populous of Italy, having an areal extent of about 1,280 km^2 and 2,65 million human inhabitants. In particular, the focus is on the area within the *Grande Raccordo Anulare (GRA)*, the highway ring surrounding the city area, that covers about 344 km^2 (68 km in circumference). The city, since the early 1960's has experienced a process of urbanization which increased the population with a settlement system characterized by intensive urban sprawl. The process saved large patches of non-urbanized vegetated areas within the GRA where, today, different forms of UA take place (e.g. urban farms, community gardens, etc.). UA can also be found in residential areas where small and medium sized plots nearby buildings may be used for food production.

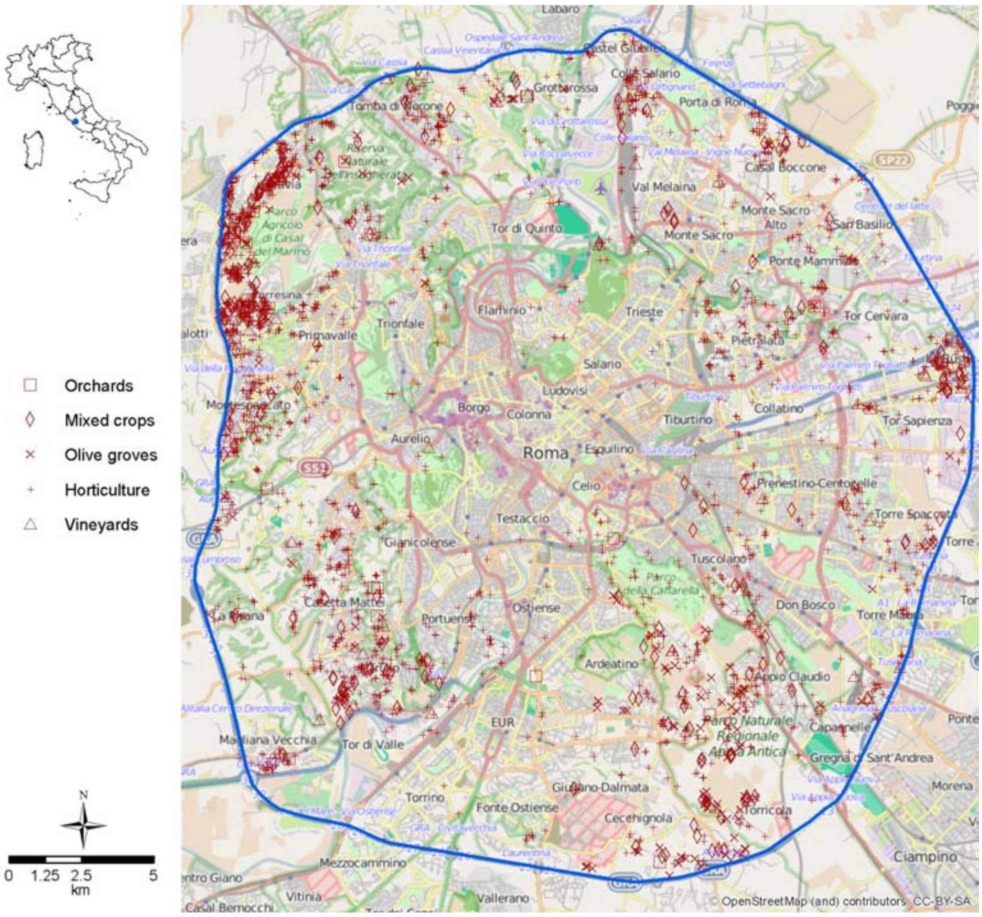

Figure 1 - Spatial distribution of the residential gardens in the area delimited by the Grande Raccordo Anulare (GRA), the highway ring surrounding the urban area of Rome. Each cultivated polygon is depicted by its centroid and classified according to five agricultural land use classes. Source: Authors elaboration.

2.2 Data

Three main types of data were used in this paper to estimate the irrigation requirement of cultivated RGs and their self-sufficiency in irrigation: climate dataset (raster format); RGs dataset (vector format) and building roof dataset (vector format).

2.2.1 Climate dataset

The climate data available from the web portal WorldClim (http://www.worldclim.org/) was selected to overcome the lack of access to climate data from local weather station in the study area. WorldClim is a set of global climate layers (climate grids), with a spatial resolution of about 1 km^2, routinely used for mapping and spatial modelling in a GIS as raster grids. Information about the methods used to generate the climate layers, the data units and formats are reported in Hijmans et al. (2005).

We extracted from the web portal the monthly precipitation and evapotranspiration dataset in raster format for a tile covering the study area. Twelve raster files, one for each month, were extracted for each climatic variable corresponding to the average values in mm computed for the period 1950-2000. The raster dataset were pre-processed with the software QGIS (http://www.qgis.org/) by using geospatial functions to assign the monthly average values of each climatic variables to the RG polygon located inside the corresponding 1 km^2 grid cell.

2.2.2 Residential gardens dataset

During the last decade some tentative for inventorying the cultivated patches in the urban area of Rome were undertaken both by public and private bodies, but most of the efforts lead to partial and incomplete datasets. In 2014 a methodology for mapping cultivated parcels within the urban area of Rome was developed by *CREA - Consiglio per la Ricerca in Agricoltura e l'Analisi dell'Economia Agraria*, the Italian agricultural research council. The method is based on the photointerpretation of the multitemporal very high resolution imagery (years: 2007 and 2013) available in Google Earth (Lupia and Pulighe, 2014). The geodatabase created contains more than 4,000 cultivated plots classified according to different typologies (e.g. residential gardens, urban farms, community gardens, etc.). Each polygon is also classified in terms of land use with one of the following classes: horticulture, mixed crops, orchards, vineyards and olive groves.

The geodatabase reports more than 2,700 residential gardens mapped in 2013 with an area that ranges from 6 to 14,000 m^2. The small to medium sized parcels are sited generally nearby buildings in residential areas while the largest ones are mainly located far from the dense residential areas. In this study, we focus only on cultivated polygons located in residential areas by defining an area threshold of 2,000 m^2 and extracting a subset of 2,631 RGs covering and area of about 720,000 m^2 (72 ha), the summary statistics are reported in Table 1.

Table 1 - Statistical values of the area (m^2) and number of parcels (N) reported by land use typology and for the whole residential gardens (RGs) dataset. The last column reports the average crop coefficient value (k_c) assigned to each land use.

Land use	*Minimum*	*Maximum*	*Average*	*Standard dev.*	*Sum*	*% of Area*	*N*	*% of N*	k_c
Orchards	100.94	1,426.41	540.92	350.23	19,473.09	2.71%	36	1.37%	0.70
Mixed crops	37.30	1,970.06	527.17	450.31	93,835.62	13.04%	178	6.77%	0.66
Olive groves	104.44	1,983.16	945.21	513.18	86,959.56	12.09%	92	3.50%	0.70
Horticulture	6.03	1,970.49	214.17	261.10	481,024.58	66.86%	2,246	85.37%	0.75
Vineyards	44.31	1,659.44	482.51	389.30	38,118.27	5.30%	79	3.00%	0.48
RGs dataset	6.03	1,983.16	273.44	335.43	719,411.12	100.00%	2,631	100.00%	-

Source: Authors calculations.

The spatial distribution of the polygons across the study area shows a strong densification toward the periphery, where a lot of unsealed areas are available, while in the city centre, dominated by artificial areas, RGs are rare or too small to be detected by the mapping methodology (Figure 1). In terms of land use, RGs are dedicated mainly to horticulture, followed by mixed crops, olive groves, vineyards and orchards; this pattern is observed both in terms of farmed area and number of plots (Figure 2). The values of crop

coefficient (k_c), to be used for estimating the irrigation requirement, were assigned to each RG by computing an average value for the irrigation season based on the crop coefficients reported in the FAO paper 56 (Allen et al., 1998).

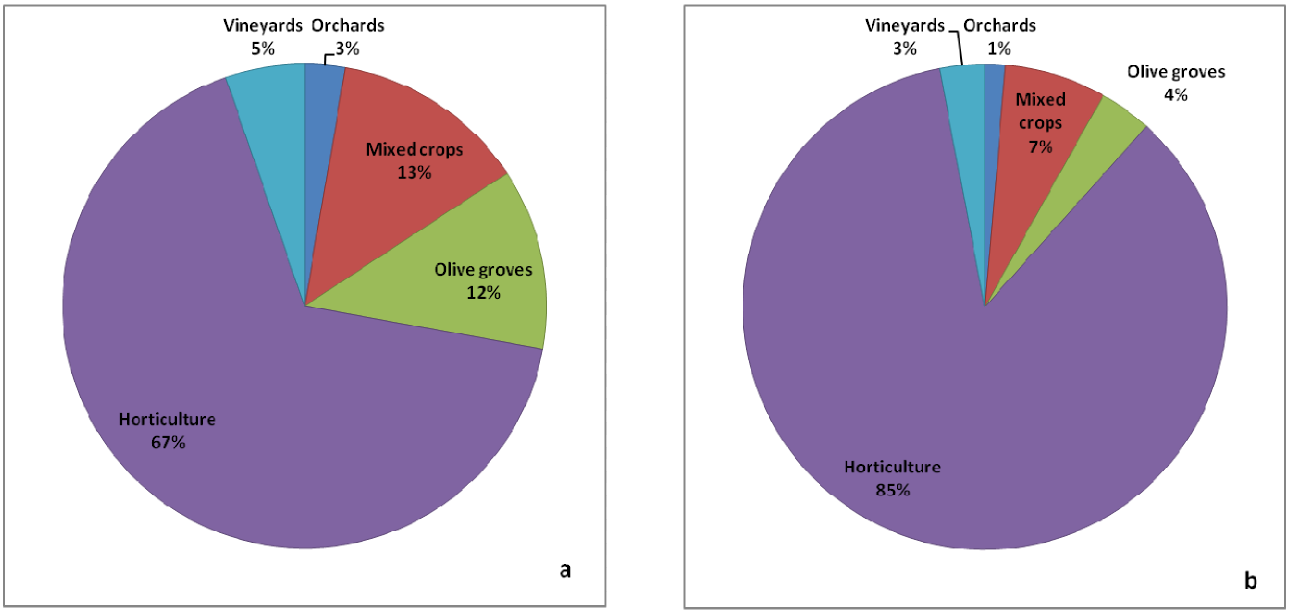

Figure 2 - Residential gardens by land use typology (percentage over the total): area (a) and number of parcels (b). Source: Authors calculations.

2.2.3 Buildings roofs dataset

The lack of updated cartographic data on buildings in the urban area of Rome was addressed by an automatic extraction method applied to a series of very high resolution (VHR) WorldView-2 monoscopic satellite images acquired in 2012. VHR optical images (≤ 1 m), such as WorldView-2, enable the detection of features like roofs in a very detailed way; they also introduce some new problems related to the large amount of information being gathered, which were not encountered with the previous sensors (Dell'Acqua et al., 2011).

To perform a classification on a monoscopic satellite image, it is mandatory to use a pansharp image (Parente and Santamaria, 2013), an image that has the geometric resolution of the panchromatic band and the radiometric information of the multispectral ones. The pansharpened image was orthorectified using 54 GPS/GNSS RTK control points equally distributed on the frame and a digital elevation model obtained from 1:2,000 scale. The expected planimetric and altimetric accuracies were, respectively, 0.05 m and 0.10 m for GCPs (Ground Control Points) and 0.4 m and 1 m for cartography. GCPs and cartography were both referred to the new Italian reference system (Barbarella, 2014). Considering the extension and the heterogeneity of the study area, we divided the image into subsets, approximately 2.5 x 2.5 km each. This step is often recommended in order to reduce the processing time required by high-dimension images, but also to optimize the classification according to different characteristics of each subset.

We then performed the classification with the object-oriented approach as implemented in eCognition Developer 8.0 (http://www.ecognition.com) that in earlier researches demonstrated to be highly accurate (Baiocchi et al. 2014). The object-oriented approach toward image analysis is based on the idea that the important information necessary to interpret an image is not represented only in a single pixel, but in meaningful image objects and their mutual relationships. The basic difference, especially with regard to pixel-based procedures, is that this technique does not classify single pixels, but rather image objects that are extracted in a previous image segmentation step; that is, it uses a bottom-up, region-growing technique,

starting with one-pixel objects. Starting at an arbitrary point in the image with one-pixel objects, and in a number of consecutive steps, the pixel objects are enlarged to bigger pixel groups (segments) until certain heterogeneity is reached. The obtained segments are optimized using three homogeneity criteria: scale, shape, and colour. Obviously, the scale parameter, which defines the mean dimension of the image object identified, plays a fundamental role in the robustness of the classification (Al Khudhairy et al., 2005). Indeed, the scale parameter must be chosen according to different situations and goals. For this reason, in this experiment, we tested the segmentation results using different scale parameters, and approximately considered the target object dimension that corresponds with the dimensions of the roof of a building. For the present study and imagery used, a scale parameter of 65 seemed to result in the best performance, but this can only be considered as a tentative guideline for future experimentations because several tests should be performed to find, case by case, the scale that best fits the specific application for the image. After the segmentation, the classification could be performed in different ways and through different steps. In this case, because attention had to be focused on the buildings class, we started by classifying vegetation using classical NDVI criteria. A detailed explanation of this phase is omitted from this article for issues of length, but a complete description can be found in a previous paper (Baiocchi et al., 2013).

A literature review revealed the concern that using the NDVI for the elimination of vegetation from further data processing steps carries the risk that the shadowed parts of the buildings will also be eliminated from the processing (Grigillo et al., 2011). For this reason, the same procedure was used to classify the shadows in the image. In this case, a predefined feature of brightness was used, so after the most appropriate threshold of brightness was chosen, the unclassified objects from previous classifications were assigned to the shadows class. For all other classes in our hierarchy, we adopted a nearest-neighbour classification because this has been deemed a proven and robust classifier. In fact, by considering identified samples as representatives for each class, the algorithm searches for the closest sample object in the feature space for each image object. In some cases, we completed the class description by designating specific parameters. For example, for the buildings class, we added a threshold regarding the extent (area > 100 m2), while for the shadows, we inserted a condition about the proximity to other classes such as vegetation or buildings (distance to buildings < 1.5 m). It is imperative that this operation be performed manually by selecting the appropriate number of samples, which usually seems to be correlated to the total number of image objects created during the segmentation; furthermore, the samples must be equally distributed over the entire image.

The building dataset extracted was saved in vector format and processed by using QGIS; each building polygon was considered coincident with the relative roof. Roof area was computed in m^2 and each roof polygon was associated by a spatial join to the nearest RG by considering the smallest Euclidean distance between the centroid of roof and RG.

3. Methods

3.1 Computing the rainwater harvestable from roofs

The estimation of the rainwater that can be collected from each roof located nearby the cultivated plots was done by using the roof size and the monthly average precipitation values for the period 1950-2000 extracted for the study area. The following equation was used:

$$RH = P_{tot} \cdot A_{roof} \cdot H_{eff} \qquad [1]$$

where RH is the amount of rainwater harvestable (m^3), P_{tot} is the total annual precipitation (m) computed by adding the average monthly precipitation, A_{roof} is the roof area (m^2) and H_{eff} is the harvesting efficiency of the system. A standard value of efficiency (60%) was attributed to the catchment area to account for leaks, wind and rainfall rates. In fact, during a slow gentle rain, with no leaks in the system, collection efficiency can

reach about 95%, while, during a very fast, heavy rain, the efficiency would be closer to 60-75 % because gutters overflow and gutters covers are overrun with water.

We made the hypothesis that the rainwater collected from roofs is stored in a water tank in the cultivated parcels and later used to irrigate the crops in the period April-September. The amounts of rainwater collectable in each RG is modulated by the roof area and gradient of precipitation of the 1 km^2 grid cell. No evaluation was performed about tank sizing and space requirements for the installation in the RG. In addition, the water collected during the whole year was considered available for the period April-September, without taking into account the water budget of the tank (i.e. the balance among irrigation demand, rainwater collected and tank overflow).

3.2 *Computing the irrigation water requirement at parcel level*

The water consumption of each cultivated parcel was assessed by computing the Irrigation Water Requirement (IWR) for the irrigation season (April-September) by assuming that parcels are in dry conditions during the autumn and winter seasons. IWR can be defined as the amount of water, net of effective precipitation, needed to fulfil evapotranspiration for maximum plant growth and yield of a given crop in a specific climate regime and at a given time of its phenology:

$$IWR = \sum_{i=4}^{9} (k_c \cdot ET_{o(i)} - P_{eff(i)}) \quad [2]$$

where k_c is the average crop coefficient defined according to the land use of each parcel, $ET_{o(i)}$ and $P_{eff(i)}$ are the reference evapotranspiration and the effective rainfall of the i-th month, both in m if IWR is expressed in m^3. The product k_c by ET_o is the crop water requirement under standard conditions (Allen et al. 1998).

The parameter P_{eff} (i.e. net of foliage interception) can be calculated for each month as (Brower et al. 1986):

$$P_{eff} = 0.8P - 25 \quad if\ P > 75 \quad [3]$$

$$P_{eff} = 0.6P - 10 \quad if\ P < 75 \quad [4]$$

where P is the precipitation in m.

To have a more realistic quantity of water to be applied to each RG we took into consideration the application efficiency of the irrigation system used by computing the Gross Irrigation Water Requirement (GIWR):

$$GIWR = \frac{1}{E} \cdot IWR \quad [5]$$

where E is the field application efficiency of the irrigation system. We computed two values of GIWR for each RG by considering two different irrigation systems: surface and localized (i.e. drip irrigation). The values of 45% and 90% (Brouwer et al., 1989) were assigned to surface and localized irrigation systems respectively.

4. Results and discussions

The total roof area associated to the RGs dataset is 388,806 m^2 (Table 2). The range of values is quite large for olive groves, mixed crops and horticulture while is smaller for orchards and vineyards. The average size is around 150 m^2 for all land use types except for orchards having smaller average values (92.36 m^2).

The annual amount of rainwater harvestable by all the roofs associated to the RGs dataset is 183,482.53 m^3 (Table 2). Results were computed through the equation [1] that is a linear relationship between the roof size and the annual amount of precipitation, therefore the same consideration done for the roof area apply on the range and average values for each land use type. The average RH values is around 70 m^3 for all land uses, except for orchards that is smaller (43.45 m^3). Overall, the average RH in the study area for each square meter is 0.47 m^3.

Table 2 - Statistical values of the roofs area (m^2) and the rainwater annually harvested (RH) from roofs (m^3). Values are reported by land use typology and for the whole residential gardens (RGs) dataset.

		Orchards	*Mixed crops*	*Olive groves*	*Horticulture*	*Vineyards*	*RGs dataset*
Roof area	*Minimum*	11.00	7.00	15.00	2.00	7.00	2.00
	Maximum	208.00	1,567.00	1,566.00	2,511.00	543.00	2,511.00
	Average	92.36	152.06	162.35	147.64	150.44	147.78
	Standard dev.	55.48	190.93	209.33	193.46	114.13	190.78
	Sum	3,325.00	27,067.00	14,936.00	331,593.00	11,885.00	388,806.00
	%	0.86%	6.96%	3.84%	85.28%	3.06%	100.00%
RH	*Minimum*	5.45	3.20	7.12	0.93	3.38	0.93
	Maximum	95.22	728.25	745.10	1,188.99	262.59	1,188.99
	Average	43.45	71.98	77.30	69.63	70.96	69.74
	Standard dev.	26.14	91.41	99.75	92.08	54.38	90.85
	Sum	1,564.23	12,813.12	7,111.64	156,397.90	5,605.63	183,492.53
	%	0.85%	6.98%	3.88%	85.23%	3.05%	100.00%

Source: Authors calculations.

The comparison of the RGs irrigation water requirement and the rainwater harvestable from roofs allows to evaluate the self-sufficiency in irrigation of RGs for each land use. Figure 3 shows the amount, in percentage over the total, of irrigation that can be provided by rain and other sources (e.g. water mains, wells), simulations are made with the two irrigation systems: low and high efficiency. Under the condition of high irrigation efficiency almost half (44%) of the polygons in the study area can be irrigated by collecting rainwater, the figure is lower with the low irrigation efficiency systems (22%). Amongst the land use types, the largest self-sufficiency is reached by horticulture for both irrigation systems, in the case of high efficiency the share of water provided by rain prevail over the other sources (57%).

Figure 4 reports the number of parcels self-sufficient in irrigation. Almost one-third of the RGs can be irrigated with rainwater if high irrigation efficiency systems are employed, while one-fifth of the RGs are self-sufficient in the case of low irrigation efficiency systems. Looking at the data at land use level, horticulture has the highest number of plots self-sufficient in irrigation: one-fifth and more than one-third, for the low and high irrigation efficiency respectively. The lowest level of self-sufficiency is associated to orchards having only 0% and 3% of self-sufficient parcels in the case of low and high irrigation efficiency respectively.

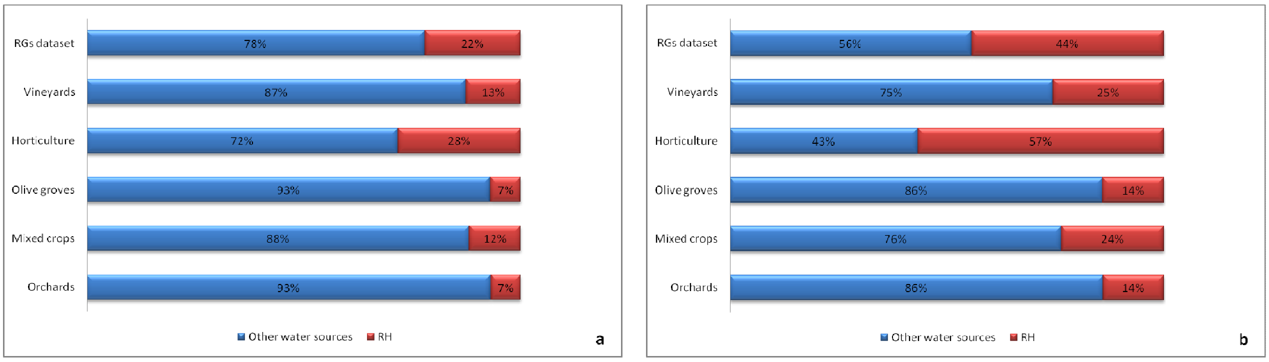

Figure 3. Share (percentage over the total) of irrigation that could be provided by rainwater and other sources for each land use typology and for the whole residential gardens (RGs) dataset. Results are computed under the hypothesis of using low (a) or high irrigation efficiency systems (b). Source: Authors calculations.

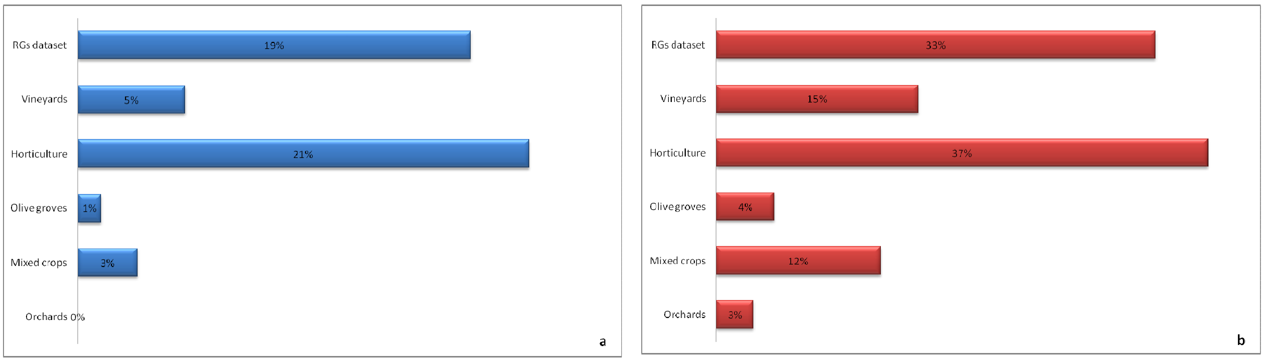

Figure 4. Number of polygons (percentage over the total), by land use typology and for the whole residential gardens (RGs) dataset, that could be irrigated without resorting to additional water sources by using rainwater. Results are computed by considering the use of low (a) and high irrigation efficiency systems (b). Source: Authors calculations.

The results obtained indicate that collecting and storing rainwater from roofs can potentially provide an alternative irrigation source to be used by the RGs located in the urban area of Rome. In particular, the use of RH can reduce the resort to other sources (e.g. water mains) with different intensity according to the type of irrigation system used (low or high efficiency) and the land use type. Interestingly, at the same time a portion of RGs can be considered self-sufficient in irrigation and no other irrigation source is needed. This findings confirm those provided by (Lupia and Pulighe, 2015) for the same study area computed by considering a fixed roof size of 100 m^2 for all RGs. We also observe that, given the amount of rainwater harvestable in the study area, beyond the impacts reduction on potable water and water abstracted from other sources, this approach has the potential to minimize storm run-off (Cameron et al., 2012; Hunt and Rogers, 2014).

However, a more precise modelling would be necessary for accurately defining strategies for urban water management. In particular, meteorological data with greater spatial resolution would improve the estimation of irrigation requirement for each parcels during the irrigation season. In addition, to verify the results obtained, the correct size of the tank to store rainwater and its water budget for each parcel should be performed by taking also into account others non-potable domestic water supply (e.g. WC flushing).

5. Conclusions

This paper has sought to address questions related to the irrigation water requirement of residential gardens with vegetables and fruit trees located in the urban area of Rome. In particular, the RGs self-

sufficiency in irrigation by using the rainwater harvestable from nearby roofs was evaluated. The assessments were done by exploiting multi-source dataset created by different methodologies to overcome the lack of data with adequate spatial resolution for the study area.

The subject have to be considered relevant due to growing interest around urban agriculture and the spreading of cultivated parcels in many metropolitan areas. In this context, the evaluation of water resources is relevant for the high water demand and the expected Climate Change impacts, especially for those cities with policies supporting UA development (Johnson et al., 2015).

The results obtained show to which extent RGs with different land use types (e.g. horticulture, orchards, etc.) can be irrigated with rainwater harvestable from nearby roofs as well as how many RGs could be self-sufficient in irrigation (i.e. no other water source is required to satisfy the irrigation requirements). More detailed studies could identify strategies to collect rainwater adapted to different types of housing and RGs. Though, to introduce these techniques it is important to raise awareness among local authorities and involve them in measures to provide information and advice to urban farmers.

The methods presented here are based on several simplifications and more sophisticated modelling would help to produce reliable estimates and precise evaluation for implementing planning strategies. However, this approach contribute to have a preliminary picture of one of the component of the water use in urban areas and can be easily applied to other cities.

6. Acknowledgements

This study was supported under the INEA project "Cultura Contadina" (http://www.inea.it/cultura-contadina).

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