SoftwareX 29 (2025) 101997

Contents lists available at ScienceDirect

SoftwareX

journal homepage: www.elsevier.com/locate/softx

Original software publication

URSUS_UHI: URban SUStainability software for detection of unfavourable areas due to the Urban Heat Island effect

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ARTICLE INFO

Dataset link: http://earthexplorer.usgs.gov, https://github.com/ursusdm/URSUS_UHI

Keywords:
Remote sensing
Disadvantaged area index (DAI)
Spatial data mining
Intelligent decision support system

ABSTRACT

Identifying the most unfavourable areas of cities, in terms of high temperatures and lack of vegetation, can help to improve urban sustainability and combat climate change. URSUS_UHI is a software that could help make decisions on which areas need priority attention in terms of adding green infrastructure to reduce temperatures. It develops a spatial data mining processes that incorporates expert knowledge to automatically detect the most disadvantaged areas in terms of higher temperatures and lack of vegetation. In this way, users such as urban planners or landscape engineers can identify the most suitable areas in which to act.

Code metadata

Current code version	v.1.0.1
Permanent link to code/repository used for this code version	https://github.com/ElsevierSoftwareX/SOFTX-D-24-00079
Permanent link to Reproducible Capsule	Not applicable
Legal Code License	GNU General Public License (GPL), version 3
Code versioning system used	Git
Software code languages, tools, and services used	R, R packages (shiny, dplyr, leaflet, raster, rf ...)
Compilation requirements, operating environments	R 4.3.1 or later
If available Link to developer documentation/manual	https://github.com/ursusdm/URSUS_UHI/blob/main/README.md
Support email for questions	francisco.rdg.gmz@uma.es

1. Motivation and significance

Numerous studies on climate change predict an overall increase in temperatures. The consequences of rising temperatures are more worrying and significant in urban areas than in surrounding rural areas. This warming phenomenon is mainly due to anthropogenic development in the urban area and the increase in built-up areas [1]. The use of construction materials that absorb most of the solar radiation and release it in the form of heat generates the Urban Heat Island (UHI) phenomenon. The UHI impacts the health and quality of life of residents directly or indirectly [2], and even affects their mortality [3]. This represents a new challenge for urban planning as the implementation of different alternatives to alleviate these problems and make cities more resilient. In this regard, the presence of Urban Green Infrastructures (UGI) contributes to the mitigation of the UHI effect [4], given that there is a clear correlation between the abundance of vegetation and the temperature of the soil surface [5].

Increasing the area with vegetation (both in quantity and in surface area), especially in the most unfavourable locations, constitutes an interesting solution [6], since it not only alleviates the effect of UHI, but also provides a further series of ecosystem services in cities [7]. Identifying potentially useful regions and deciding the most convenient actions to be carried out is part of the land use planning problem, which is a demanding search and optimisation task [8].

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https://doi.org/10.1016/j.softx.2024.101997
Received 6 February 2024; Received in revised form 14 November 2024; Accepted 25 November 2024
Available online 5 December 2024

In recent years, several studies have been conducted on the role vegetation plays in decreasing temperatures in urban environments [9]. Many of them rely on remote sensing, but the methodology used to obtain the results is *non-automatic* [10–12]. This means that the researchers have to download the satellite images and perform the calculations themselves to obtain the values of the indicators used. In addition, intensive pre-processing is required to prepare the data before calculations can be performed (such as conversion between coordinate systems, extraction of multispectral band information or data cleaning).

Two remotely sensed indicators that can reveal relevant information in this context are:

(a) Normalised Difference Vegetation Index (NDVI), a numerical vegetation index that ranges from −1.0 to 1.0, with values below 0 in the case of water. Values over 0.2 indicate the presence of vegetation, depending on the amount and physiological state of the plant cover [13,14]. A negative correlation between NDVI and temperature has been observed by several researchers [15].

(b) Land Surface Temperature (LST) that represents the temperature measured at the surface. It is an excellent indicator to take into account to quantify the UHI effect in a city [16].

However, the combination of both indicators has not been previously used for determining the most unfavourable areas of a city. These relations have been explored before [17], including NDVI-LST seasonal and annual correlations, but not in terms of favourability.

The significant increase in the amount of information available in recent years has led to the use of new techniques that allow the automatic extraction of valuable and relevant information. In this way, artificial intelligence-driven technologies have been purposed as facilitators to Sustainable Development Goals (SDGs) [18] because they enable *automation*, traceability and optimisation. It is worth noting that one of these SDGs is to make cities sustainable.

Contribution

The primary motivation for developing URSUS_UHI software is that it could help improve urban sustainability and mitigate climate change by automatically identifying the most unfavourable areas due to the Urban Heat Island (UHI) effect in any city. In this way, urban planners will be able to know which areas should be prioritised for incorporating elements of urban green infrastructure (UGI).

Even when temperature and vegetation measurements (LST and NDVI) can reveal useful information on their own, it would be very interesting to find a way to combine them and thus identify unfavourable urban areas. URSUS_UHI calculates, *automatically*, a new index designed by experts that uses combined information from both variables (LST and NDVI) to quantify the level of deterioration. It has been named the Disadvantaged Area Index (DAI).

This new index, DAI, combined with the knowledge acquired by an unsupervised learning process (performed by the k-means clustering algorithm [19]) produces an enriched information to detect the most unfavourable areas in the area of interest.

A prototype version of URSUS_UHI has been used to analyse sixteen cities in Spain to discover the most unfavourable areas due to the UHI effect [20]. The experts, in the field of urban greening and biosystems engineering, highlighted the usefulness of having this tool and how it had accelerated and improved the standard processes. The main reason is that, once the satellite images of interest have been downloaded, the tool performs all the pre-processing task and calculations to discover the most unfavourable areas. The evaluation task is also automated, allowing for easy validation of the results.

Nowadays, the software has reached a stable version and has been made available as open-source at https://github.com/ursusdm/URSUS_UHI [21].

Experimental setting

URSUS_UHI performs a data mining process from the data provided by the user, following some steps summarised in Fig. 1. The interaction with the software is very simple. The user downloads the image of the region where the city to be analysed is located, selects the area of interest and execute the process. The tool then transforms the data, combines the information and visualises the results with respect to the most disadvantaged areas due to the UHI effect.

Related work

Some studies have estimated the optimal locations for UGI and the potential impact that can be expected in specific cities based on the UHI effect, but, for that, the researchers performed each of the tasks one by one in a non-automated way. Therefore, these methodologies of estimating optimal locations are not easily scalable, reproducible, or exportable to other cities.

Table 1 summarises the different traditional features used and calculated in some related research.

The potential of spatial data mining and how easy it is to integrate it into an automated process is known, so it seems appropriate to develop a methodology that can analyse data from remote sensing sources and automatically identify unfavourable areas of a city. The implementation of this methodology results in the software proposed in this paper, URSUS_UHI. It takes information from multispectral satellite images and applies a spatial data mining process to extract knowledge. In addition to automatically retrieving and organising the information, the methodology incorporates the calculation of a new index and a clustering process to detect a set of optimal locations where UGI can be created. The last row of Table 1 highlights that the software developed covers all the features studied and does so automatically.

2. Software description

The URSUS_UHI software is a free tool that combines remote sensing, satellite image processing, data analysis, modelling methods and expert-designed indices to determine the most unfavourable areas due to the Urban Heat Island (UHI) effect.

These elements are relevant to the different phases of a Data Mining (DM) process, in which the modelling stage is a key phase. The modelling phase uses mathematical models to identify patterns in the data [31], and involves the selection of appropriate machine learning algorithms (such as classification or clustering) [32]. In the development of the proposed tool, the selection of algorithms has been directed to the clustering task, what constitutes a common application of artificial intelligence in data mining [31], also when learning from spatial data.

2.1. Software functionalities

URSUS_UHI offers a comprehensive set of functionalities designed to understand the state of cities with respect to the UHI effect, while identifying the most unfavourable areas. The main functionalities are described in Fig. 2. Internal functionalities are described in next subsection, and those that can be directly invoked by the users are listed below:

- Upload Landsat −8 images previously downloaded from some other source (like USGS EarthExplorer).
- Select the image of a city from the previous uploaded images.
- Define the urban area of interest by cropping the area on a map. This map is an auxiliary map with higher resolution than the loaded Landsat −8 image, which helps to identify elements and facilitates correct cropping.
- Request for image information processing to obtain the results and display them in the application.

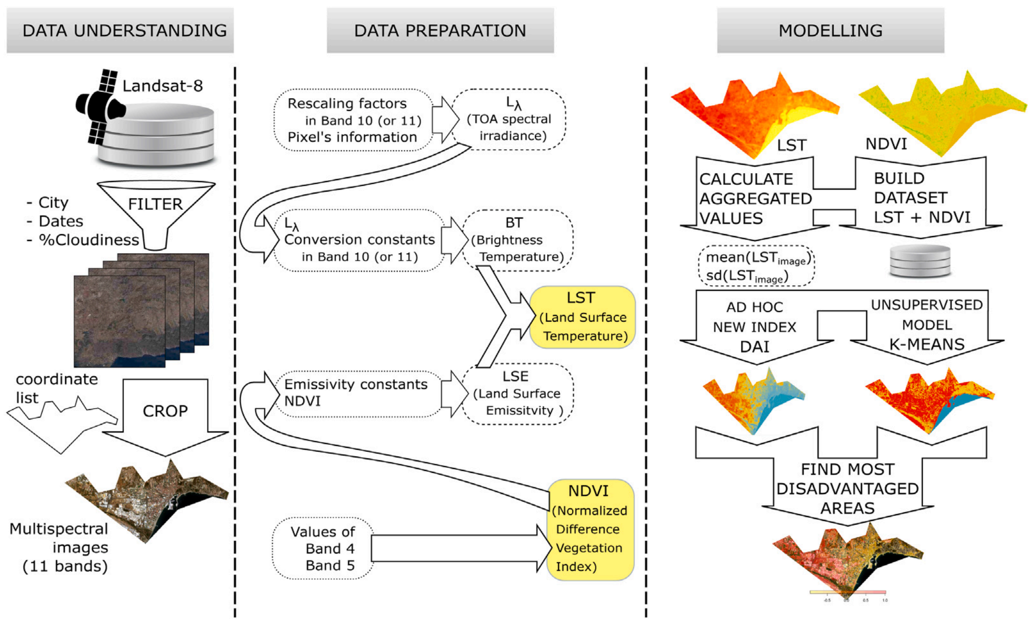

Fig. 1. Data mining, CRISP-DM methodology. User selects the appropriate image and crops the area of interest. Data preparation step does transformations to get Land Surface Temperature (LST) and Normalised Difference Vegetation Index (NDVI) images. These images are processed to extract relevant information and identify the most disadvantaged areas due to the UHI effect.

Table 1
Features provided by different related works.

	Temperature	Land classification	Optimal location	Automated methodology	Software availability
Sun et al. (2018) [22]	✓	✓	–	–	–
Li and Zou (2019) [23]	✓	✓	–	–	–
Masoudi and Tan (2019) [24]	✓	✓	–	–	–
Asadi et al. (2020) [25]	✓	✓	–	–	–
Rahaman et al. (2022) [26]	✓	✓	–	–	–
Fernández et al. (2015) [27]	–	–	–	✓	–
Bartesaghi-Koc et al. (2019) [28]	–	✓	–	✓	–
Velázquez et al. (2019) [29]	–	–	✓	–	–
Nesticò et al. (2022) [30]	–	–	✓	–	–
URSUS-UHI (this proposal)	✓	✓	✓	✓	open-source

2.2. Software architecture and implementation

The main components of the URSUS_UHI system are described below and Fig. 3 briefly shows the architecture and interactions of the main human, hardware and software components of the system.

2.2.1. User

Anyone can be a potential user of this tool, but the stakeholders are people or administrations involved in city planning, such as urban planners or landscape engineers. They are the human component that requests the required functionalities and visualises the results of the processing carried out by the URSUS_UHI web server through a web browser. Details of the main functions that can be requested by the user can be found in Section 2.1.

2.2.2. Web application: client

The client-defined interface has been specifically designed to make the tool accessible to a wide range of stakeholders, who do not require in-depth domain knowledge. Its implementation is defined in the function *ui* within the script *app.R*.

The web application constitutes the interface through which the users interacts with the system, allowing them to request the required functionality. It can be accessed through a web browser and includes the essential elements to capture the input in an easy way, while providing all the maps necessary to visualise the output.

Therefore it is responsible for rendering the graphical components that allow the user to interact with the system (buttons, maps, images selector, etc.). During this interaction, users can provide input data to the system (such as an image with the selected city or a cropped area to define the region of interest). Once the input is entered, the processing of the data starts and the result is displayed. For this purpose, different maps are calculated and showed: the main result, highlighting the most unfavourable points in the area of interest, is part of the main screen; the auxiliary maps with intermediate calculations have been placed into another tab.

2.2.3. Web application: server

The web server has the role of backend, and takes care of all the processing to carry out the functionality requested by the user through the web application. Its implementation is defined in the function *server* within the script *app.R*.

To satisfy the requested functionalities, the web server uses two components defined in the scripts *aux.R* and *UHI.R*

Script aux.R. The main functions of general purpose implemented by this script are the following:

- *utmToGPSExtent()* converts GPS coordinates to UMT coordinates to match the selected area on a world map (which has higher quality) with the Landsat −8 image uploaded (which contains the necessary bands to do the process).

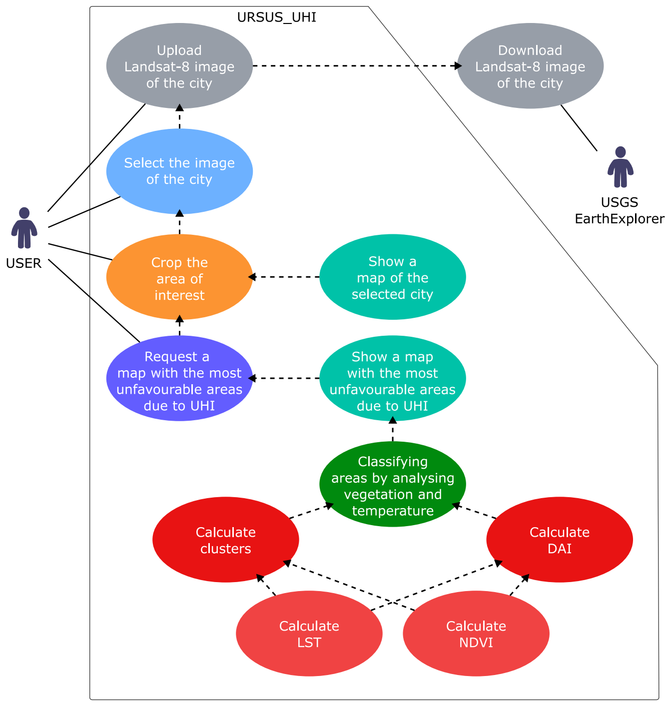

Fig. 2. Use case diagram. The following model describes the main functionalities of the system; both the internal functions and those offered to the user through the interface.

- *cropSelectedAreaFromLandsatImage()* crops the selected area of interest from the Landsat −8 image.
- *readMetadata()* reads metadata of the satellite image of the selected area.
- *readMultibandRasterLayer()* generates a multi-band raster layer with information about the spectral bands of the Landsat −8 image of the selected area.

The last two functions allow the system to process the calculation of NDVI and LST from the area of interest defined by the user.

Script UHI. R. The functions implemented in this script are for calculating variables related to the Urban Heat Island (UHI) effect domain. The details about these calculations and processes (NDVI, LST, clustering, DAI) are available at [20]. The most relevant functions are listed below:

- *calculateNDVI()* implements the calculation of the NDVI map from the multiband raster layer of the cropped satellite image.
- *calculateLST()* uses some other auxiliary functions to calculate the LST map from the multiband raster layer of the cropped satellite image.
- *normalizeNDVI()* and *normalizeLST()* normalise the corresponding maps to prepare them for applying the clustering algorithms. For the normalisation process, the mean image value of has been subtracted from each NDVI or LST pixel and divided by the standard deviation of the NDVI or LST map.
- *calculateDAI()* calculates the Disadvantaged Area Index (DAI) for every pixel in the cropped image.
- *getClusters()* applies the k-means algorithm to find three clusters (k=3) using the NDVI and LST information of every pixel. A model is generated and each point in the map is classified into one of the three different groups based on how favourable those areas were in terms of temperature and vegetation presence.
- *getMoreDisfavourableAreas()* determines the most unfavourable cluster using aggregated DAI values for each cluster. It then returns the DAI values for each point in the most unfavourable cluster.

2.2.4. Landsat −8 images database

Landsat −8 imagery is the core data source used by the system to discover hidden information. The main input to the tool are Landsat −8 satellite images with 30x30m/pixel terrain coverage that can be downloaded free of charge for any city. They are composed of a series of spectral bands and metadata that allow the software to perform the necessary calculations to obtain the variables used in the process described: NDVI and LST. From these variables, the system can proceed to calculate the clusters and the DAI of the most unfavourable areas.

2.2.5. Leaflet maps

It provides the web application interface with a layer that allows the user to interact with a world map and define the area of interest. The packages *leaflet* and *leaflet.extras* are used to provide such interaction.

2.2.6. Other packages shared in the architecture

There exist some other R packages that are used in the tool which use is not limited to a specific component:

- *raster:* package has been used for the processing and visualising satellite images like displaying maps, cropping or doing coordinate system conversion.
- *dplyr:* package has been used to prepare the processed data in the format the clustering algorithms require.
- *shiny:* package allows the development of web applications for data mining projects by offering functions that allow you to design dashboards. It has been used to implement the interface between the client and the application and to develop the web application.

3. Illustrative examples

In this Section, an example is explained. This example is used in the manual available with the source code, where a detailed step-by-step guide is provided. One explanatory video describing a more complete process is available at the same site.

3.1. Unfavourable areas in Málaga (Spain)

A Spanish city, Malaga, has been selected to illustrate the functionality of the URSUS_UHI tool. Malaga is located in southern Spain (see Fig. 4) and has a population of 578,000 inhabitants. It is located on the coast, between two river valleys, with a mountain range to the northeast and the Mediterranean Sea to the south. Temperatures are milder (although with higher relative humidity). Even so, they can reach up to 35 °C.

A Landsat −8 satellite image (acquired in 2023) was downloaded using USGS EarthExplorer. This image contains 30-meter multispectral data from the Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) onboard the Landsat −8 satellite. Then, this image was uploaded to the URSUS_UHI tool (button "Folder selector" on the top left of Fig. 5).

The image was cropped to fit the area of interest, defining the desired coordinates of the city. The upper world map in Fig. 5 was used interactively to obtain this user definition. Thus, only the relevant parts of the images were processed, with the computation delimited to the desired areas.

Once the information on the Landsat −8 image was processed (using the "Process urban area" button below the world map), the result was shown at the bottom of the window (see Fig. 5). In this map, the white pixels are not a cause for attention because they are outside the unfavourable class (such as green areas, rivers or the sea). Inside the cited unfavourable class, the intensity of the disadvantage is indicated with one scale of colours: red tones are the most unfavourable regions in the area of interest.

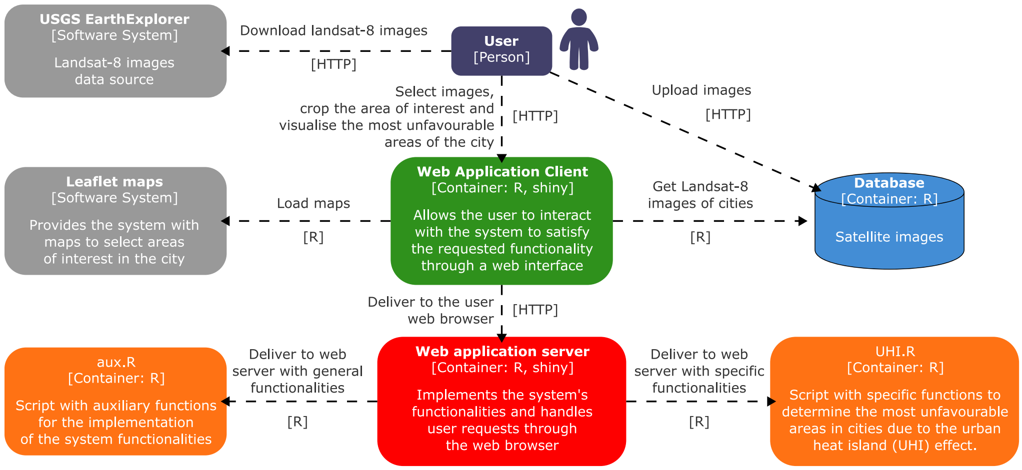

Fig. 3. System architecture detailing the main components and their interactions.

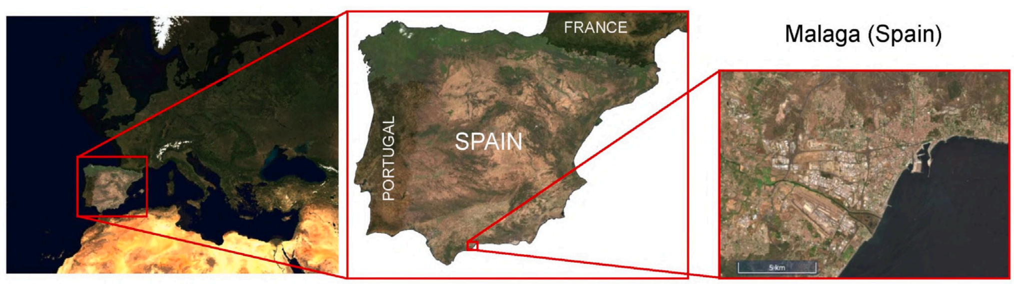

Fig. 4. Location of Malaga in Spain (Europe). RGB image downloaded from the Spanish Geographic Institute (IGN) with the license CC-BY 4.0. http://www.ign.es.

Generally, the areas showing higher DAI values correspond to industrial areas with big metal or concrete buildings and scarce or no vegetation. The airport, in the southwest part of Malaga, and the nearby industrial zone are good examples. Bareland areas also tend to be catalogued as unfavourable and mainly found on the outskirts. The effect of the water bodies [33], like the sea, is also evident.

3.2. Limitations and areas for improvement

The main drawback of the developed tool is that it relies on the satellite images selected by the user and fed to the system. If any of them are inadequate (i.e., a high percentage of clouds or missing or incorrect information in many pixels), it can affect the final result presented by the tool.

The resolution of the images is another crucial factor, and the potential of this tool could be increased by using images from other satellites with a higher resolution or when combined with other tools used for detecting urban vegetation [34].

Another problem arises due to the low temporal resolution of satellite imagery [35] since the information is only acquired once a day and simultaneously every day. Therefore, it does not consider the LST evolution during the day. This problem can be alleviated by using images of the same city from different satellites passing at different times.

Regardless, it is also important to note that, even when satellite-based observations of surface UHI are likely to overestimate actual daytime impacts, the images clearly indicate surface thermal contrasts [35], making them suitable for use in the tool developed.

The validation of unsupervised classification in remote sensing represents a significant challenge. While internal metrics can be employed, external validation or comparison with known data is preferable. However, this is a complex task largely due to the lack of ground truth or labelled data [36]. An alternative method for assessing the quality of the results is based on expert judgement, which can be employed to compare the new information with other sources [20], such as the Urban Atlas Copernicus project [37]. Nevertheless, although it is feasible to validate the results, this task is not currently automated by this software. One way to overcome this limitation could be the incorporation of multitemporal remote sensing images, which could even detect changes over time [38].

4. Impact

The URSUS_UHI programme allows to:

1. automate the processes of detecting the most unfavourable areas in cities in terms of lack of vegetation and high temperatures;
2. provide public administrations with a free tool that can help identify the best areas in which to add urban green infrastructures to reduce the UHI effect;
3. combine machine learning and expert knowledge that have been validated and tested in the fight against climate change.

Having a simple and free tool that automates a manual (and complex) process consisting of locating the optimal areas in which to add UGI could accelerate the identification process and locate many different options. Another noteworthy aspect of URSUS_UHI is that its usefulness and the quality of the results generated have been validated by experts. The tool has been used (in its prototype version) to study sixteen Spanish cities [20] by a group of experts in the field of urban greening.

In addition to the above mentioned issues, new research questions can be pursued as a result of the development of this tool, mainly in the context of optimisation. Stakeholders are interested in designing urban green infrastructure that makes the best use of resources (time and space) at minimum cost. These questions are derived from collaboration with experts and the current state of the tool suggests promising results.

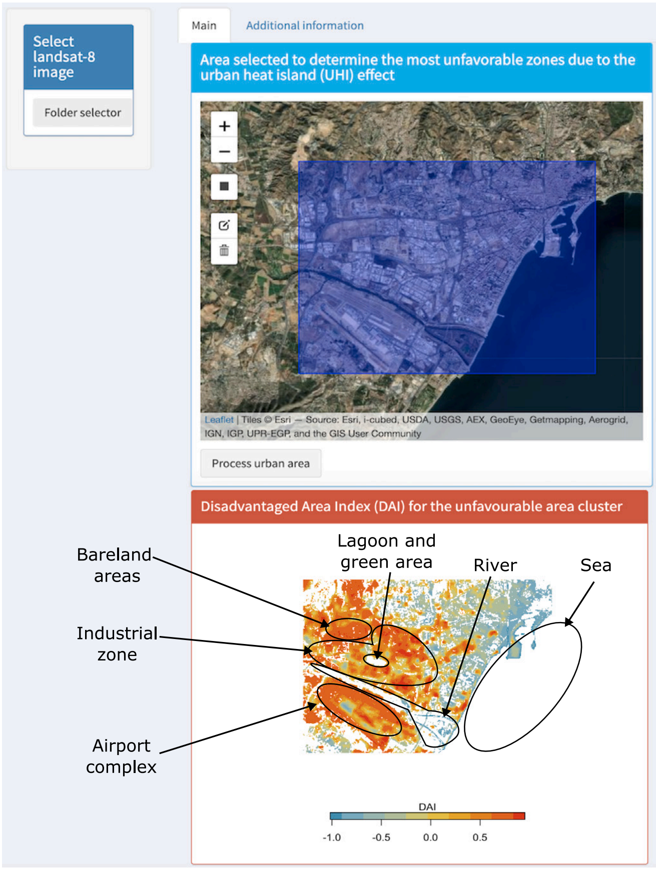

Fig. 5. URSUS_UHI main tab. It includes the input and output in the same tab. In this example, the map shows the city of Malaga (Spain) with the cropping area of interest (input) and the map of the most unfavourable areas due to the UHI effect (output). Some labels describing the territory have been added.

5. Conclusions

An intelligent tool based on data mining processes has been developed: URSUS_UHI. It uses machine learning and expert knowledge to automate a complex process that is traditionally carried out manually. It determines the most unfavourable regions in any area of interest in a city, attending to the urban heat island effect.

Experts, including urban greening and biosystems engineers, mathematicians, and landscape architects, have evaluated the quality and validity of the tool. They have applied the methodology in different cities, analysed the results obtained, and verified their coherence. Once the tool's results had been validated in some cities, it was extended to more cities: sixteen cities in Spain were processed, and the results were automatically calculated.

It can be concluded that URSUS_UHI is a valid alternative to speed up the processes of improving urban sustainability and a valid way to combat the effects of climate change. It could help public administrations and urban planners to identify areas where it is a priority to add green infrastructure elements in order to reduce high temperatures. Its simplicity of use, as well as its user interface designed for all types of users, could enhance its integration. It can be of interest in spatial planning, especially when conducting environmental impact assessments.

This software could be the starting point for other tools for providing further applications such as determining what kind of green infrastructure (green roofs, vertical gardens, etc.) would be the most appropriate to reduce the high temperatures in the most unfavourable areas. Also other developments could focus on the evaluation of different alternatives of available urban infrastructure (such as rooftops, car parks or facades) which could be used to allocate more vegetated areas.

CRediT authorship contribution statement

Francisco Rodríguez-Gómez: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Data curation. **José del Campo-Ávila:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Conceptualization. **Domingo López-Rodríguez:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Conceptualization. **Luis Pérez-Urrestarazu:** Writing – review & editing, Writing – original draft, Validation, Resources, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

F.R.-G. acknowledges the financial support provided by project RTI2018-095097-B-I00 at the 2018 call for I+D+i Project of the Ministerio de Ciencia, Innovación y Universidades (Spain) (MCIU), which funded his position during the development of this work. D.L.-R. also acknowledges the financial support given by the project VALID, with reference PID2022-140630NB-I00 and funded by MCIU/AEI/10.13039/501100011033 (Spain). The publication of this article was made possible through financial support from project VALID (PID2022-140630NB-I00, MCIU/AEI/10.13039/501100011033 (Spain)).

Data availability

Landsat-8 satellite images are freely available from Earth Explorer (USGS, Department of the Interior, U.S.A. http://earthexplorer.usgs.gov). The URSUS-UHI source code (released under the GNU General Public License v3.0) and instructions can be downloaded from the following repository: https://github.com/ursusdm/URSUS_UHI.

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