SIAPARTNERS

Urban Heat Islands Study

November 2023

Summary

Last year, we published two articles “**The countless opportunities unlocked by satellite images**” and “**From sensors to display, a journey towards usable satellite images**” providing readers with a comprehensive overview of satellite images. In the first piece, we delved into the world of satellite imagery and discussed various aspects such as its applications, technological advancements, and its impact on different industries. In the second, we presented the post-processing to be applied to raw satellite data before mapping the resulting image onto a common map system. Through our articles, we aimed to educate readers about the vast potential of satellite imagery and how it continues to shape our understanding of the world.

Building upon our previous exploration of satellite images, in this whitepaper, we delve into a concrete case study: urban heat islands. Recognizing the importance of this phenomenon and its implications for urban environments, we have created this whitepaper to provide a comprehensive understanding of the subject.

In a **past whitepaper**, we delved into the causes and effects of heat islands, examining the factors that contribute to their formation, and the subsequent impacts on human health, energy consumption, and overall urban climate. Additionally, we explored the potential mitigation strategies that can be employed to alleviate the adverse effects of heat islands. We also explained how an efficient mobilization of artificial intelligence can allow us to better understand the situation across a territory and support the political decision making to address it.

In this whitepaper, we shift our focus towards the role of satellite imagery in studying heat islands. We will showcase the specific satellite sensors and image processing operations utilized to detect and monitor heat islands, highlighting their capabilities in mapping surface temperatures and identifying vulnerable areas. Then, we will take a deeper dive into the computational aspects of studying heat islands. We will explore the intricacies of calculating surface temperatures, mapping heat distribution, and generating visual renderings that aid in visualizing and circling heat islands. Additionally, we will highlight how we can use these detections to compute vulnerability indices useful for urban planning and public health interventions.

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Introduction

Urban Heat Islands

The physical phenomenon of urban heat islands (UHI) consists of an increase in air and surface temperatures within urban areas, at the street or neighborhood level, compared to peripheral or rural areas.

According to a study published by climatologists from Drias - Météo-France on June 16, 2022[1] which identifies the French cities that will suffer the most from particularly high summer temperatures from 2040 onwards, forty-five of them will experience at least ten additional abnormally hot days during the summer. In order to avoid becoming unbearable, our city centers must adapt to this well-identified and particularly unpleasant phenomenon during periods of intense heat. Which will increase in frequency and intensity due to global warming.

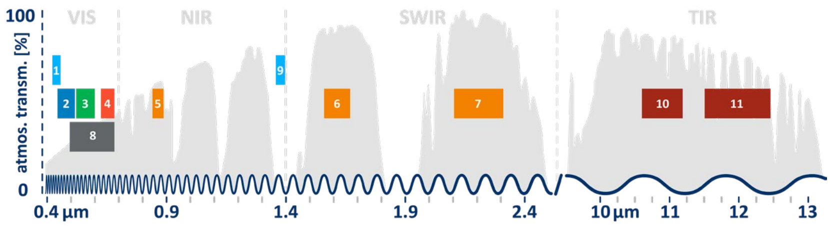
Sia Partners is a next-gen consulting firm that invests heavily in data science and explores the possibilities offered by artificial intelligence to meet its clients' use cases and needs. Faced with the challenges of climate change, Sia Partners is enriching its service offering to support private and public actors in establishing their transition strategy. In this regard, we have developed a methodology for analyzing satellite images to identify and characterize urban heat islands in order to better understand the existing situation and inform decision-making.

Landsat 8 images

Urban heat islands (UHIs) are areas within urban regions that are warmer than the surrounding rural areas due to the absorption and retention of heat by urban surfaces and human activities.

Landsat 8 satellite imagery can be used to detect and delimit urban heat islands by analyzing the thermal properties of the surface.

Landsat 8 is the product of a collaboration between NASA and the United States Geological Survey (USGS). It is a satellite equipped with a suite of sensors that can collect data in various spectral bands, including visible, near-infrared, shortwave infrared, and thermal infrared. Landsat 8 has 11 spectral bands:



BAND	SPECTRAL	WAVELEN. [µm]	GEOM. [m]	SENSOR
1	aerosols	0.435 – 0.451	30	OLI
2	blue	0.452 – 0.512	30	OLI
3	green	0.533 – 0.590	30	OLI
4	red	0.636 – 0.673	30	OLI
5	NIR	0.851 – 0.879	30	OLI
6	SWIR-1	1.566 – 1.651	30	OLI
7	SWIR-2	2.107 – 2.294	30	OLI
8	pan	0.503 – 0.676	15	OLI
9	cirrus	1.363 – 1.384	30	OLI
10	TIR-1	10.600 – 11.190	100	TIRS
11	TIR-2	11.500 – 12.510	100	TIRS

The bands are used for various purposes, such as vegetation monitoring, cloud and snow cover mapping, atmospheric correction, and mineral identification. The panchromatic band provides high-resolution imagery with 15 m spatial resolution, while the rest of the bands have 30 m spatial resolution. The thermal infrared bands provide data on surface temperature, which is useful for monitoring and studying natural resources, and analyzing the impacts of natural hazards, such as wildfires.

(1) Publication of the results of the study in Le Figaro:
https://www.lefigaro.fr/sciences/les-villes-les-plus-menacees-par-l-explosion-des-jours-et-des- heatwave-nights-20220616
(2) Freie Universitat Berlin online course, Landsat 8 course: https://blogs.fu-berlin.de/reseda/landsat-8/

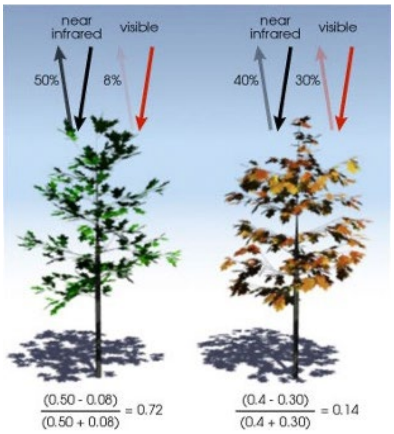
Extraction of new bands

There are many different indices that can be extracted from satellite bands, depending on the sensor and the specific bands used. Each index is designed to highlight a specific feature or characteristic of the Earth's surface, such as vegetation, water bodies, or urban areas, and can be used for a variety of remote sensing applications, including land use and land cover mapping, environmental monitoring, and natural resource management.

Vegetation detection

A popular remote sensing metric for assessing the health and density of vegetation is the **Normalized Difference Vegetation Index (NDVI)**. For photosynthesis, plants - especially healthy ones - absorb much in the visible spectrum, particularly the red, whereas near-infrared (NIR) energy from the sun is reemitted by leaf cells. The following formula is used to determine NDVI:

$$NDVI = \frac{NIR - Red}{NIR + Red}$$



Source: Nasa

NDVI values range from -1 to 1 with positive values indicating the presence of vegetation. Values close to 1 indicate dense vegetation, while values close to 0 represent sparse vegetation or bare soil. Values less than 0 can indicate water or clouds.

NDVI is commonly used in remote sensing applications to map vegetation and monitor crop growth, detect changes in land use and land cover, and to study the impacts of climate change and environmental factors, such as drought and flooding, on vegetation.

Water detection

The Normalized Difference Water Index (NDWI) is a remote sensing index that is used to identify and map open water bodies such as lakes, rivers, and wetlands. NDWI is based on the fact that open water bodies reflect more near-infrared light than they do green light.

NDWI is calculated using the following formula:

$$NDWI = \frac{Green - NIR}{Green + NIR}$$

NDWI values range from -1 to 1, with positive values indicating the presence of water. Values close to 1 indicate the presence of open water, while values close to 0 indicate the presence of vegetation or other non-water surfaces.

NDWI is commonly used in remote sensing applications to map and monitor the extent and changes of water bodies, for water resources management, wetlands and coral reef health monitoring, and for the detection of floods and droughts.

NDWI could be used as a complementary tool to other indices like MNDWI (Modified NDWI), and other water indices like AWEI (Automated Water Extraction Index) and OI (Open Water Index) to obtain more accurate results.

Urban detection

There are several different indices that can be used to identify and map urban areas, including the **Normalized Difference Built-Up Index (NDBI)**, the Normalized Difference Impervious Surface Index (NDISI), and the Urban Index (UI). NDBI is one of the most popular indices and is calculated using the following formula:

$$NDBI = \frac{SWIR1 - NIR}{SWIR1 + NIR}$$

NDBI values range from -1 to 1, with positive values indicating the presence of built-up surfaces such as roads, buildings, and other urban structures. Values close to 1 indicate densely built-up areas, while values close to 0 indicate sparsely built-up areas or natural surfaces.

Another index used is the Urban Index (UI) where SWIR1 is replaced by SWIR2:

$$UI = \frac{SWIR2 - NIR}{SWIR2 + NIR}$$

Urban indices can be used in remote sensing applications to map and monitor the extent and changes of urban areas, for urban planning and management, and for environmental monitoring.

Land Surface Temperature

As mentioned above, infrared satellite systems use specialized sensors to detect infrared radiation emitted from the Earth's surface. The thermal infrared radiation (TIR) region encompasses both the middle-wave (MWIR) and longwave infrared (LWIR).

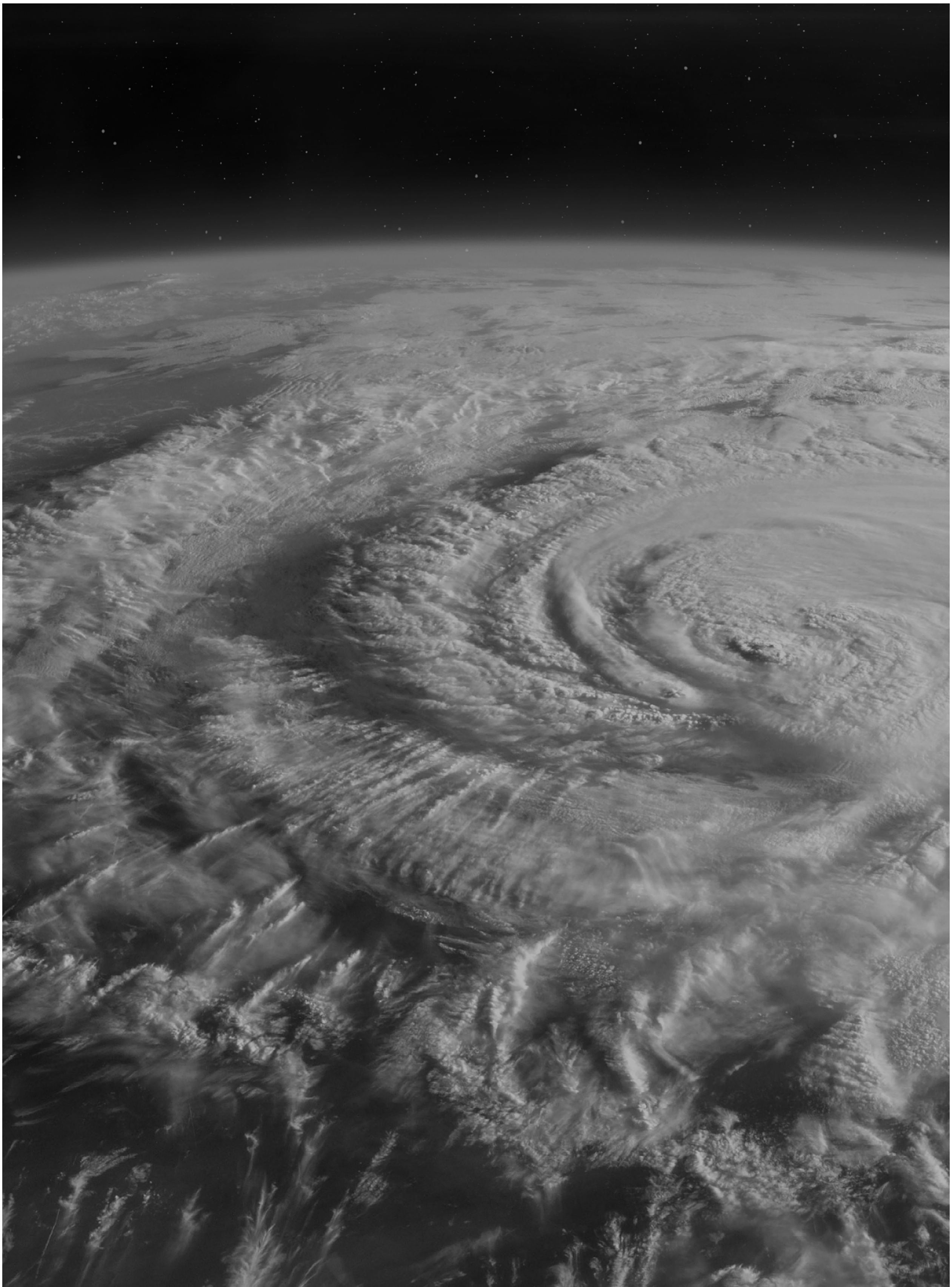
Land Surface Temperature (LST) is a crucial parameter for understanding the Earth's energy balance and climate. It is frequently used in a wide range of applications, such as tracking changes in land use and land cover, assessing the effects of urban heat islands, examining water use, and tracking the impacts of climate change on the planet's surface.

Using Landsat8 OLI/TIR's LST has many advantages for monitoring the Earth's surface, including its ability to detect temperature changes at a high spatial resolution (30 meters resolution), its ability to detect temperature changes over time (2 weeks resolution), and its ability to detect temperature changes in areas where ground-based measurements are not feasible or available.

Google Earth Engine

Google Earth Engine (GEE) is a cloud-based platform for analyzing and visualizing satellite and aerial imagery. It is developed and maintained by Google, in collaboration with a number of academic and research institutions.

GEE provides access to a massive archive of satellite imagery, including images from Landsat, Sentinel, and other satellite missions. The platform also includes a wide range of tools for analyzing and visualizing the imagery, including image processing algorithms, machine learning models, and interactive visualization tools. GEE also provides access to other types of data such as weather forecasts, digital elevation models, and population datasets.



Urban Heat Islands **detection and characterization**

Heat islands are caused by multiple factors, and their prediction requires combining different types and sources of data and searching for patterns that lead to this phenomenon. First, we need to detect existing heat islands using the surface temperature from Landsat 8 images, then we characterize the detected islands using satellite images and external data.

Image generation

We begin by extracting a collection of Surface Reflectance (SR) Landsat 8 images acquired between April and November of years 2018 to 2022. The SR data are images that have been corrected for atmospheric effects and that are also available in GEE. Limiting the dataset to April and November ensures cloudless images and strong heat islands. It is possible to limit the dataset to a shorter period to study the evolution of heat islands through time or the effect of some counter measures. However, when looking to detect urgent zones in need of immediate action, it is better to enlarge the temporal scope of the dataset.

Then, we apply a mask to each image to remove all pixels corresponding to clouds before averaging all the pixels corresponding to the same coordinate across the dataset. The resulting image is a cloudless and aggregated image that covers almost the entirety of the world. Then, that image is cropped to the area of interest defined by a polygon of coordinates.

Land Surface Temperature computation

To compute Land Surface Temperature (LST) from Landsat 8 imagery, several steps are necessary.

Brightness Temperature

First, when using raw images, (Level-1 Data Product) Digital Number (DN) values of the thermal band B10 should be converted to radiance values using the radiometric calibration coefficients provided by the metadata[3]:

$$L_\lambda = M_L Q_{cal} + A_L$$

where:

- ***L_λ*** *is the TOA (top of atmosphere) spectral radiance*
- ***M_L*** *is the Band-specific multiplicative rescaling factor from the metadata = RADIANCE_MULT_BAND_10*
- ***A_L*** *is the Band-specific additive rescaling factor from the metadata = RADIANCE_ADD_BAND_10*
- ***Q_{cal}*** *are the Quantized and calibrated standard product pixel values (DN)*

After that, Planck's law equation is used to convert radiance values to brightness temperature.

$$BT = \frac{K_2}{\log\left(\frac{K_1}{L_\lambda} + 1\right)} - 273.15$$

Where:

- ***BT*** *is the brightness temperature in degrees Celsius*
- ***L_λ*** *is the TOA spectral radiance*
- ***K_1*** *is the Band-specific thermal conversion constant from the metadata = K_1_CONSTANT_BAND_10*
- ***K_2*** *is the Band-specific thermal conversion constant from the metadata = K_2_CONSTANT_BAND_10*

However, since we use the Landsat 8 Surface Reflectance catalogue in GEE, the provided band B10 is already the calibrated top-of-atmosphere (TOA) Brightness Temperature, but rescaled for memory reasons. The calibration parameters are provided by USGS[4]. Which means:

$$BT = ST_{B_{10}} \cdot 0.00341802 + 149$$

Emissivity

Next, we need to compute emissivity, which is a measure of the ability of a surface to emit thermal radiation. Emissivity is usually estimated using land cover classification or emissivity libraries. It can also be estimated using other Landsat 8 bands, however with less accuracy. In this study we use a vegetation cover method described by[5]. First, we compute the vegetational index (PVI) using the following formula:

$$FVC = \left(\frac{NDVI - NDVI_{bare}}{NDVI_{veg} - NDVI_{bare}}\right)^2$$

Where $NDVI_{veg}$ and $NDVI_{bare}$ are the NDVI values of completely bare and fully vegetated pixels, respectively. These values can be used from literature or

(3) Ermida, Sofia & Soares, Patrícia & Mantas, Vasco & Göttsche, Frank-M & Trigo, Isabel. (2020). Google Earth Engine Open-Source Code for Land Surface Temperature Estimation from the Landsat Series. Remote Sensing. 12. 1471. 10.3390/rs12091471.
(4) USGS website; Using the USGS Landsat Level-1 Data Product: https://www.usgs.gov/landsat-missions/landsat-collection-2-level-2-science-products
(5) USGS website; Using the USGS Landsat Level-1 Data Product: https://www.usgs.gov/landsat-missions/using-usgs-landsat-level-1-data-product

computed by extracting the minimum value (bare) and maximum value (veg) of the NDVI band of the satellite image.

Emissivity values over vegetated areas at any given time, may then be derived using the

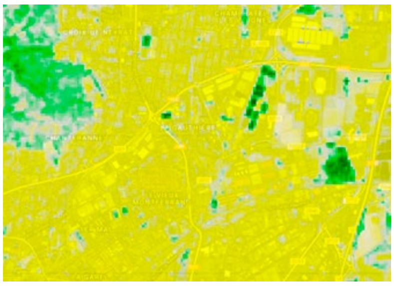
Vegetation-Cover method, which is defined as:

$$\varepsilon = FVC \cdot \varepsilon_{b,veg} + (1 - FVC)\varepsilon_{b,bare}$$

Where $\varepsilon_{b,veg}$ and $\varepsilon_{b,bare}$ are the emissivity of vegetation and bare ground for a given spectral band b.

NB: It is important to note that emissivity values can vary depending on the surface materials and conditions, so using an emissivity library or other data sources specific to the area of interest is recommended.

EMISSIVITY MAP OF AN AREA
OF CLERMONT-FERRAND



Land Surface Temperature

The formula used to calculate Land Surface Temperature (LST)[6] from Brightness Temperature (BT) and Emissivity (ε) is known as the Stefan-Boltzmann Law. The formula is:

$$LST = \frac{BT}{1 + \left(\frac{\lambda}{\rho} * BT\right) * \ln(\varepsilon)} - 273.15$$

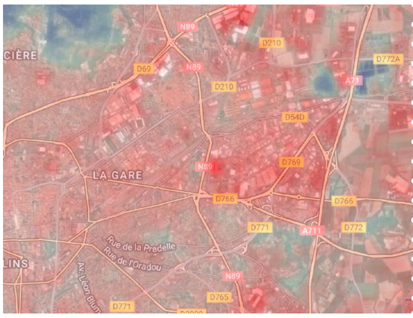
Where:

- ***λ** is he average wavelength of band 10*
- ***ρ = h * $\frac{c}{\sigma}$** in which σ is the Boltzmann constant, h is the Plank's constant and is the velocity of light c*
- ***LST** is the Land Surface Temperature in degrees Celsius,*
- ***BT** is the Brightness Temperature in Kelvin,*
- ***ε** is the Emissivity, and ln is the natural logarithm.*

The Stefan-Boltzmann Law is based on the relationship between the total radiant heat energy emitted by a surface and its temperature. This formula is commonly used in remote sensing applications, particularly for estimating LST from thermal remote sensing data.

Summary

BRIGHTNESS TEMPERATURE
OF AN AREA OF CLERMONT-FERRAND



LST OF AN AREA OF CLERMONT-FERRAND

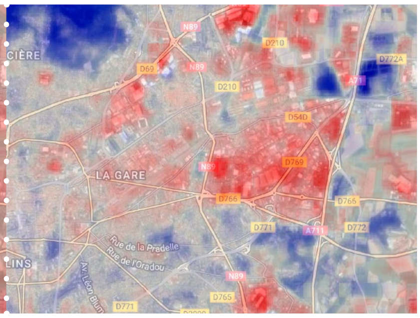


DIAGRAM OF LST CALCULATION USING THE TIR BAND

Input image

Landsat 5 TM/Landsat 8 Collection 1 Tier 1 Raw Scenes

Calculate Top of Atmosphere Radiance

$$L_\lambda = ML \cdot Q_{cal} + AL$$

Where *ML* is the band-specific multiplicative rescaling factor from the image metadata, *AL* is the band-specific additive rescaling factor from the image metadata, and Q_{cal} is the quantised and calibrated standard product pixel values (*DN*).

Convert Top of Atmosphere image to Top of Atmosphere Brightness Temperature (°C)

$$T_B(°C) = \frac{K_2}{\ln\left(\frac{K_1}{L_\lambda} + 1\right)} - 273.5$$

Where K_2 is the calibration constant (*K*), K_1 is the calibration constant (*W/m² *sr*µm*) and L_λ is the spectral radiance.

Calculate NDVI

$$NDVI = \frac{NIR - R}{NIR + R}$$

Where *NIR* is *B4/B5* and *R* is *B3/B4* for *L5/L8.*

Calculate proportional vegetation

$$P_v = \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}}\right)$$

Where $NDVI_{max}$ = 0.5 and $NDVI_{min}$ = 0.2.

Calculate surface emissivity

$$\varepsilon = 0.004 \cdot P_v + 0.986$$

Where P_v is the proportional vegetation. Emissivity obtained using method from Sobrino et al. (2004).

Calculate Surface Temperature (°C)

$$LST(°C) = \frac{T_B}{1 + \left(\frac{\lambda \cdot T_B}{\rho}\right) \cdot \ln(\varepsilon)}$$

Where λ is the central wavelength of emitted radiance, $\rho = h*c/\sigma = 1.438*10^{-2}$ *m*°C*, with σ is the Boltzmann constant ($1.38*10^{-23}$ *J/°C*), *h* is the Planck's constant ($6.626*10^{-34}$ *J*s*), c is the light velocity (2.998*108 *m/s*).

(6) GIS website; How to Use ArcGIS Pro to Calculate Land Surface Temperature (LST) from Landsat Imagery: https://www.gislounge.com/how-to-use-arcgis-pro-to-calculate-land-surface-temperature-lst-from-landsat-imagery/

Urban heat islands detection

Setting the temperature threshold

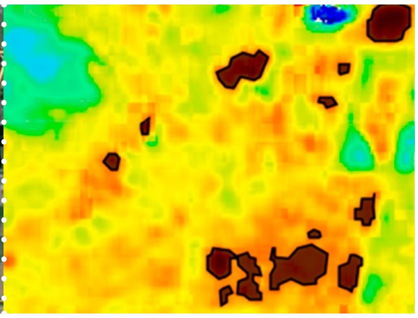
Now with the LST computed, we can detect urban heat islands. By using a clustering algorithm on the LST values of the image, we create 3 categories corresponding to low, medium, and high temperatures. A simple K-Nearest Neighbors algorithm is enough for this purpose. The third quantile of LST values of the high temperature category is used to fix the threshold needed to limit heat islands. However, the threshold can also be fixed empirically.

UHI contour detection

By filtering tempertures less than the computed threshhold, a mask image is created where hot pixels are labeled as 1. Then the Connected Component Analysis (CCA) method is applied to identify and group the UHIs within the mask. This technique involves examining the mask's pixel values and recognizing clusters of connected or adjacent pixels that share the same value. Each of these clusters are assigned a unique label, essentially grouping the pixels belonging to a single urban island together. By applying this method, we obtain a labeled mask where each island is distinguished by its own label or identifier. This allows us to easily perform subsequent analyses or operations on each island, such as measuring their properties or isolating them for further processing.

Now that individual UHIs are identified, we compute each contour, simplify their geometries to get smooth polygons, and filter the UHIs smaller than a fixed area.

SATELLITE IMAGE OF THE REGION OF INTEREST



LST MAP OF THE REGION SUPERPOSED BY THE DETECTED URBAN HEAT ISLAND POLYGONS

Urban heat islands characterization

Describing UHIs in detail to help identify their causes and prioritize them according to their impact can provide added value.

The algorithm puts out a feature collection of geometries corresponding to UHIs, each feature with a set of properties. The properties include the UHI area, perimeter, centroid, maximum temperature, and mean NDVI, NDWI and NDBI values. The feature collection can be used to further analyze and visualize UHIs in the AOI. In the following table, we indicate concrete examples of further variables that we can measure:

Physical variables
.Size of the urban heat island
.Geographic coordinates
.Maximum temperature
.Temperature difference with areas near the UHI
.Topography
...

Explanatory variables
.Rate of vegetation and protected areas
.Distance to roads
.Urban density
.Building types
.Building energy consumption categories
.Socio-demographic variables on the sensitivity of the area
...

Going further: **UHI potential index**

Urban heat islands have been a major concern for urban planners and policy-makers due to their adverse impacts on human health and the environment. In this regard, a correlation analysis between UHI detections and explicative variables mentioned above can provide valuable insights into the potential drivers of UHIs.

By examining the correlation coefficients between these variables and UHI detections, it is possible to identify the key factors contributing to UHIs in a particular area. Additionally, by using these correlation coefficients, it is also possible to create a new index of UHI potential that can be used to predict the likelihood of an area becoming a UHI in the future. This index can be useful in developing effective urban planning strategies and policies aimed at mitigating the impacts of UHIs. For example, if the index indicates that a particular area has a high UHI potential, planners may consider implementing measures such as increasing green spaces, promoting the use of reflective surfaces, or encouraging the use of energy-efficient building materials.

Study of the effectiveness **of UHI counter measures**

The Oasis course project was selected in October 2018 as part of the «Innovative Urban Actions» call for projects, a European Union initiative funded by the European Regional Development Fund-ERDF. This European initiative helps urban authorities to experiment with bold and innovative solutions to urban challenges. Ten Parisian schools have been selected to participate in this project between 2019 and 2021[7]. We study the impact of this project on two schools: Tandou and Emeriau kindergartens.

The Tandou kindergarten

The Tandou project started in July 2020 and ran until October 2020. The Tandou schoolyard was repurposed into a versatile, recreational space with:

- *An undergrowth area for playing with additionnal trees and vegetation as well as sliding structures.*
- *A garden with new trees and a vegetated pergola in front of the glass building.*
- *New learning supports such as a vegetable garden.*

The Emeriau kindergarten

From July 2020 to October 2020, a construction site transformed the old school yard into an «Oasis» yard with the following additions:

- *Water management*
  - *Water collector*
  - *Rainwater directed to permeable planted surfaces*
- *Biodiversity*
  - *2 trees planted*
- *Recreational facilities*
  - *Playful climbing and sliding mound in cushioning shavings, and a tobogan*
  - *Living wicker tunnel and a wicker hut*
  - *Via ferrata*
  - *River*

Before and after project study

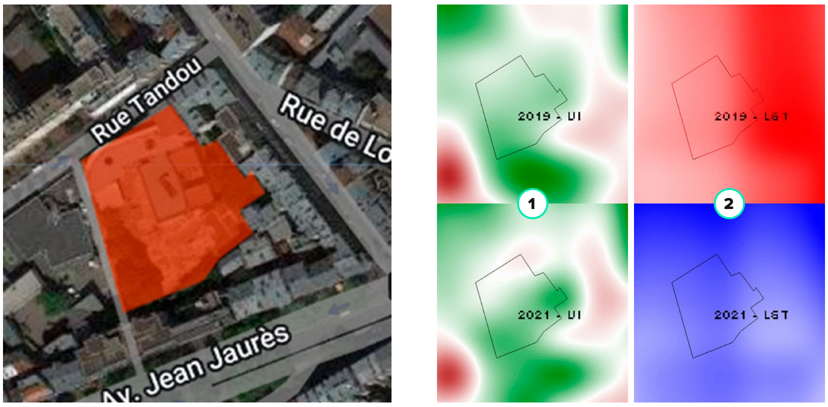
We begin by setting up the area of interest using a hand-made boundary of each school. The satellite views in the following graphs are centered on the defined geometries to provide a focused display.

We then filter and process satellite imagery from the Landsat 8 Surface Reflectance dataset. The filtering is based on the spatial intersection with the defined geometry, a specific date range (a year before and a year after the Oasis project), and a maximum

(7) CAUE website; LE FEDER URBAN INNOVATIVE ACTIONS COURS D'ÉCOLES OASIS: https://www.caue75.fr/content/le-feder-urban-innovative-actions-cours-d-ecoles-oasis

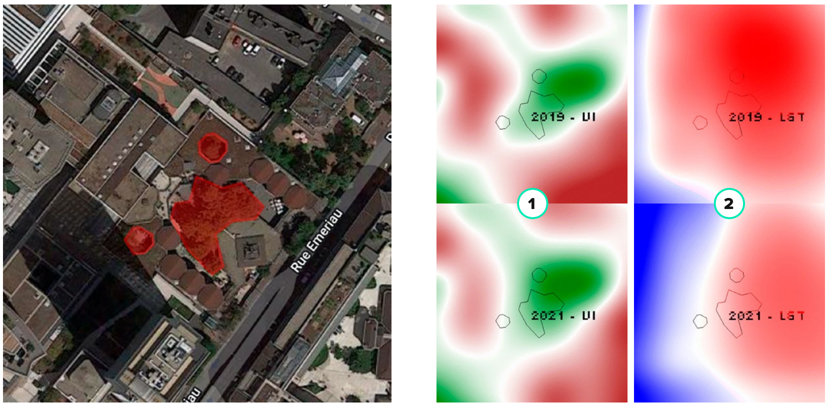
SATELLITE IMAGE OF THE TANDOU SCHOOL

One of the oasis schools of the european erdf project innovative urban action.
1 map of the urban index (NDBI) and **2** of the local temperature (LST) around the school before (2019) and after (2021) the works.



SATELLITE IMAGE OF THE EMERIAU SCHOOL

One of the oasis schools of the european erdf project innovative urban action.
1 map of the urban index (UI) and **2** of the local temperature (LST) around the school before (2019) and after (2021) the works.



cloud cover threshold. Additional bands, such as the Normalized Difference Vegetation Index (NDVI), the Urbain Index (UI) and Land Surface Temperature (LST), are calculated and added to the images.

To assess the changes before and after the construction works in 2020 within the filtered dataset, image composites are generated for each distinct observation year (2019, 2020, and 2021). These composites represent the mean value of the selected bands for each respective year. Subsequently, the composites of 2019 and 2021 are normalized using the 2020 composite as a reference.

The normalization process involves subtracting and dividing the pixel values of the pixel values of the 2019 and 2021 composites with pixel values of the 2020 composite. By applying this normalization, the resulting images allow for visualizing the variations in selected bands before and after the construction activities that occurred in 2020. This analysis enables the identification and comparison of changes in the observed features, providing insights into the impact of this project during that period.

To visualize the processed data, the code applies visualization parameters to the image collection and overlays textual annotations on each image, indicating the corresponding year. The images are blended with an outline of the defined geometry and stored in separate collections for different parameters (e.g., LST - Land Surface Temperature and UI - Urban Index).

Finally, we create filmstrips from the image collections. The resulting visual outputs can be used to observe temporal patterns and changes in LST and UI within the area of interest.

Within the neighborhood, both schoolyards became a new biodiversity relay point.

The generated GIFs provide a visual representation of the changes observed before and after the Oasis project in the surrounding area. Prior to the project, the images display higher Land Surface Temperature (LST) and Urban Index (UI) values, indicating increased heat and urbanization in the region. Moreover, the Normalized Difference Vegetation Index (NDVI) values appear lower, indicating less vegetation coverage. However, in the year following the project, the visuals illustrate a noticeable decrease in LST and UI values, suggesting a reduction in heat and urban intensity. Additionally, the NDVI values exhibit an increase, indicating an improvement in vegetation growth. These visual observations demonstrate the potential positive impact of the Oasis project on the local environment, including lower temperatures, reduced urbanization, and enhanced vegetation cover.

Conclusion

The tool developed by Sia Partners demonstrated that the use of Landsat 8 images has proven to be an effective tool in detecting and characterizing urban heat islands. The data obtained through these images and other data sources can provide valuable insights into the extent and severity of heat islands in urban areas, as well as the effectiveness of countermeasures to mitigate their impact.

With the continued growth of urbanization and the increasing threat of climate change, it is essential that we continue to explore new technologies and methods for monitoring and managing urban heat islands.

By working with city planners, policymakers, and community members, and leveraging the power of remote sensing technology, we can create more sustainable, resilient, and livable cities for all.

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