Shanghai's *One city nine towns* paradigm: assessment of the attempt to avoid conurbation. SHORT TECHNICAL REPORT TEMPLATE – EARTH OBSERVATION EXAM 2024 (Module B)

Filippo, Bissi – 233327

ABSTRACT

The city of Shanghai has witnessed one of the most intense urbanization phenomena in the history of cities over the last 30 years. This has led to an astonishing real estate growth (S. He, F. Wu, 2005, p. 7) that has nearly saturated previously unbuilt areas in both the city centre and the outskirts. To prevent urban sprawl and conurbation with neighbouring towns, the municipality implemented the "One City, Nine Towns" model. This strategy aimed to avoid the complete saturation of free land areas by following the urban planning theories of satellite cities and urban ecology proposed by Patrick Gaddes in the late 18th century (F. Bissi, 2008, p. 97). The objective of this paper is to examine whether this policy has effectively preserved the un-built areas that separate the main urban centres and hold an ecological significance for the ecosystem on which the city of Shanghai depends.

1. INTRODUCTION

In 2015 the author of this paper, driven by an unstoppable attraction to megacities, travelled to Shanghai to undertake a Double Degree in Urban Planning at Tongji University. During the year I lived in Shanghai, I had the opportunity to witness the city's frenetic development firsthand, and my background in urban planning enabled me to understand this phenomenon deeply.

My Chinese thesis[1] focuses on the historic district in downtown Shanghai and the attempt carried out by local authorities to replicate this type of settlement, in a modern way, in the satellite cities around Shanghai. In my thesis I focused on the satellite town of Pujiang, located about 20 km south of downtown Shanghai, in the Minhang district (fig. 1).

Figure 1. Shanghai downtown, Pujiang Town and Minhang district.

In fact, over the past 30 years, Shanghai has experienced one of the strongest and quickest urban growth phenomena, and the municipality has had to manage and guide this growth. The "One City, Nine Towns" policy aims to establish a primary urban core, Shanghai, and nine well-defined satellite towns located several dozen kilometres away (M. Gallo, 2016, pp.80-84). The objective of this policy is to preserve the natural areas between the cities and avoid urban sprawl. Pujiang is one of these nine towns (fig. 2), designed in 2001 by the renowned architect and planner Vittorio Gregotti for 100'000 inhabitants (L. Spagnoli, 2012, p. 555).

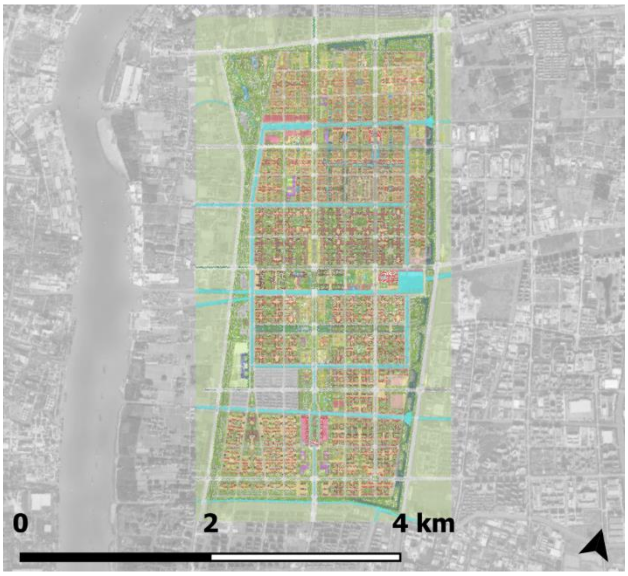

Figure 2. Pujiang new town masterplan by Vittorio Gregotti.

Even in 2016, when I lastly left Shanghai[2], this policy unfortunately did not seem to have had the desired effects, as sprawl and conurbation phenomena between Shanghai and the satellite towns, among which Pujiang, were already evident. Eventually after 2016 I had not the chance to verify if this problem has been resolved through appropriate demolitions and land recovery, and over the last years, I have always wondered whether this has occurred, or not.

The aim of this paper is to present the analyses carried out to assess this still-open question.

Within this framework, the technical analyses here reported have been carried out considering a timeframe spanning from 2016,

[1] Thesis: Filippo Bissi (2018), Lilong. An historical legacy and an opportunity of development for the future, Tongji University

[2] The thesis is dated 2018 because I had to come back to Shanghai in 2018 to get graduated after having obtained a given amount of credits from Polimi

year of departure of the author from Shanghai, until nowadays, every 2 years. Thus, the whole following analysis will focus on the following time thresholds: 2016, 2018, 2020, 2022 & 2024, for the area of Minhang district, where the town of Pujiang is located (fig.1).

2. MATERIALS AND METHODS

List of the acronyms:
- GIS: geographic information system
- GRASS: for the porpoise of this paper a set of raster, vector, and geospatial processing engines integrated into Qgis.
- MNDWI: Modified Normalize Difference Water Index
- NDBI: Normalize Difference Built-up Index
- P/GIS: Process performed only using Qgis for the sake of this paper
- P/GIS/PY: Process performed using Qgis for the sake of this paper, however the code to perform the analysis in Python has been developed and it is available on GitHub and linked in the notes
- P/PY: Process performed only using Python for the sake of this paper, the code is available on GitHub and linked in the notes
- QGIS: Quantum GIS software
- RGB: Red Green and Blue
- SACP: Semi-Automatic Classification Plugin
- SAVI: Soil-Adjusted Vegetation Index

Technical scope
The scope of this exercise is to use satellite multispectral images in order to perform multitemporal analysis in order to verify the land-use evolutions hence answer to the question of the scope.

Data planning
As stated in the introduction the analysis is focusing on the Minhang district, which roughly has an extension of 20 x 10 km. This choice has been made in order to better appreciate the possible changes occurring around the satellite town of Pujiang instead of confining the analysis to Pujiang's borders. Moreover, the Minhang district has an interesting shape "bridging" from the most central part of the city to the outskirts (fig. 1), thus it can offer a privileged overview of the conurbation phenomena by definition.

Data procurement
Given the dimension of the area of study and the chosen time thresholds the best choice of provider under the point of view of temporal and spatial resolution is Sentinel 2 (A. Lefebvrep et al, p. 2), thus all data have been downloaded through SACP (P/GIS/PY)[3],[4]. The specific used products are the following:
- RT_L1C_T51RUQ_A003947_20160325T024649_2016-03-25
- RT_L1C_T51RUQ_A005263_20180310T024751_2018-03-10
- RT_L1C_T51RUQ_A015416_20200218T023746_2020-02-18
- RT_L1C_T51RUQ_A025998_20220227T024821_2022-02-27
- RT_L2A_T51RUQ_A045417_20240303T024839_2024-03-03

All images have been chosen in the same season (only in February and March to guarantee similar vegetation conditions and thus pixel values).

Data pre-processing
- In the downloading phase has been applied the DOS1 preprocessing atmospheric correction, and all listed above product have a 0% cloud coverage, thus no further cloud masking preprocess action has been performed.
- A band set procedure has been performed in order to obtain 5 RGB multiband layers through the use of the *i.group* tool of GRASS (P/GIS).
- An image registration procedure has been performed in order to align geometrically all the data sources through the use of the tool *Align raster* provide by Qgis (P/GIS).
- A histogram manipulation procedure has been undertaken and specifically the histogram matching process to alter the value distribution of the years 2018, 2020, 2022 and 2024 using as a unique reference the year 2016 (P/PY)[5],[6].

Data processing
- A supervised classification has been performed with the Random Forest classifier, through the use of 5 training datasets[7] generated manually for each time period in Qgis with three classes: built-up areas, non-built-up areas and water. The ground truth elements have been generated balancing their elements count, individual size and their cumulative size (in this framework water area coverage is less compared to other classes). The areas have been calculated through the function *@area* of the raster calculator and checked their cumulative area through the use of the *Summarize* tool. The supervised classification for the five thresholds has been performed through Python (P/PY)[8].
- An accuracy assessment has been carried out through the generation of a confusion matrix per each year of the analysis (P/PY)[9].
- A post classification filtering has been performed through GDAL *sieve tool* with a size of dilatation of 10 (P/GIS)[10],[11].

Data post-processing
- A series of analysis[12] onto the output sieved data have been performed[13] in order to understand the classified pixels annual distribution changes (P/PY).
- A change detection process has been performed (P/GIS)[14] between year 2016 and year 2024, and the output data have been analysed (P/PY)[15].
- A set of cross-scale maps have been produced highlighting different set of aspects for the sake of the visual representation of the exercise reported in this paper.

[3] Code: Sentinel2 availability products viewer
[4] Code: Sentinel2 available data processor & downloader
[5] Code: Histogram matching
[6] Bands comparative histogram between each year threshold with 2016
[7] Training datasets for Random Forest classifier
[8] Code: Random Forest supervised classification & accuracy assessment
[9] Confusion matrices
[10] SACP – Sieve tool documentation
[11] Outputs of sieve process
[12] Data analysis histogram outputs
[13] Code: Data analysis histogram generation
[14] Three are the classes considered (built, un-built, water). To perform the change detection first of all the value of the first time-threshold (2016) have been multiplied by 4, and then a difference has been performed with the last time-threshold (2024) using its original values. This allowed to obtain 9 univocal output values for each change.
[15] Code: Change detection output analysis

3. RESULTS DISCUSSION

The analysis led to the expected results under a technical standpoint for the following reasons which is useful to consider while watching the figure 3:

- The built-up ratio constantly grows along the years
- The non-built-up ratio decreases inversely proportional to built-up ratio
- The water ratio remains the same along the years

Of course, listed above consideration are a generalization of the common evolution trends of this kind of cities, even if we need to be fully aware of the possibility of the opposite behaviour, for instance in case of demolishment and land recovery, river tunnelling / extensions, artificial lakes creation and natural disasters in general.

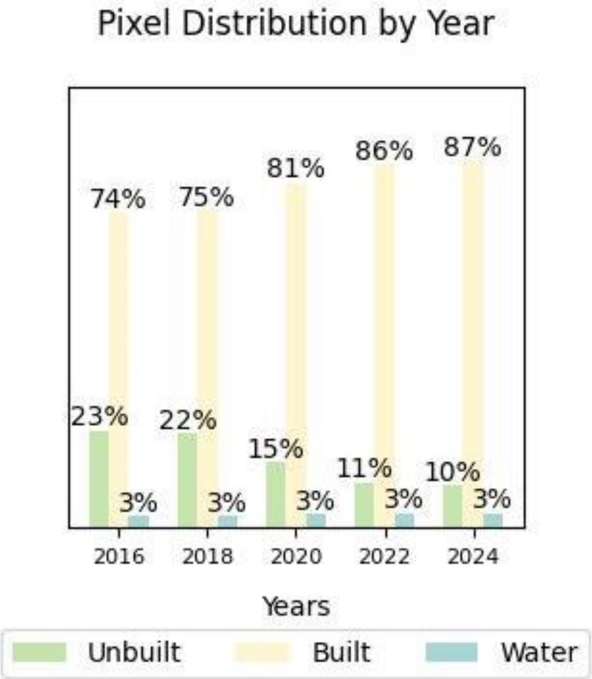

Figure 3. Pixel distribution percentage by year

What shown in figure 3 represents the multitemporal percentage growth which can be easily converted into a spatial-measurements in hectares by only multiplying the number of pixels classified in a given class by their area, where the pixels size is 0,01 ha and the total amount of pixels is 10’017’100.

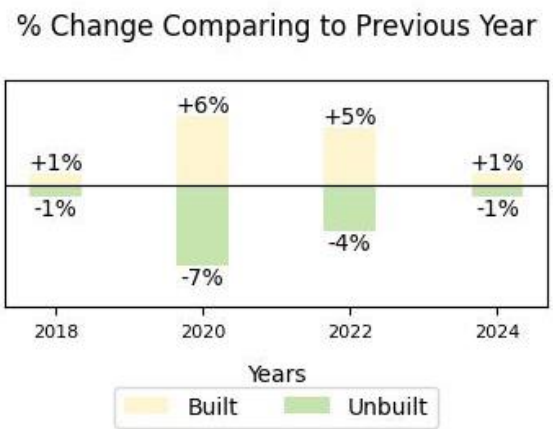

Figure 4. Annual changes of the percentage comparing to the year before

Despite the satisfactory technical result, the expected results of the overall analysis were slightly different. In fact, as mentioned, already in 2016 the effects of the “One city nine town”, aiming at avoiding conurbation, where not visible at all; a clear process of conurbation was instead clearly ongoing. Moreover, the construction growth rate was deeply examined while drafting my thesis, and there reported. Thus, the bi-annual increase of built-up areas was expected to be higher than the actual result reported in figure 4.

Through the analysis of the confusion matrices (see footnote n.9) we can state that the analysis of how the multitemporal Rgb Sentinel 2 images have been classified through the Random Forest classification is satisfying. We can further confirm this assessment by visually analysing figure 5.

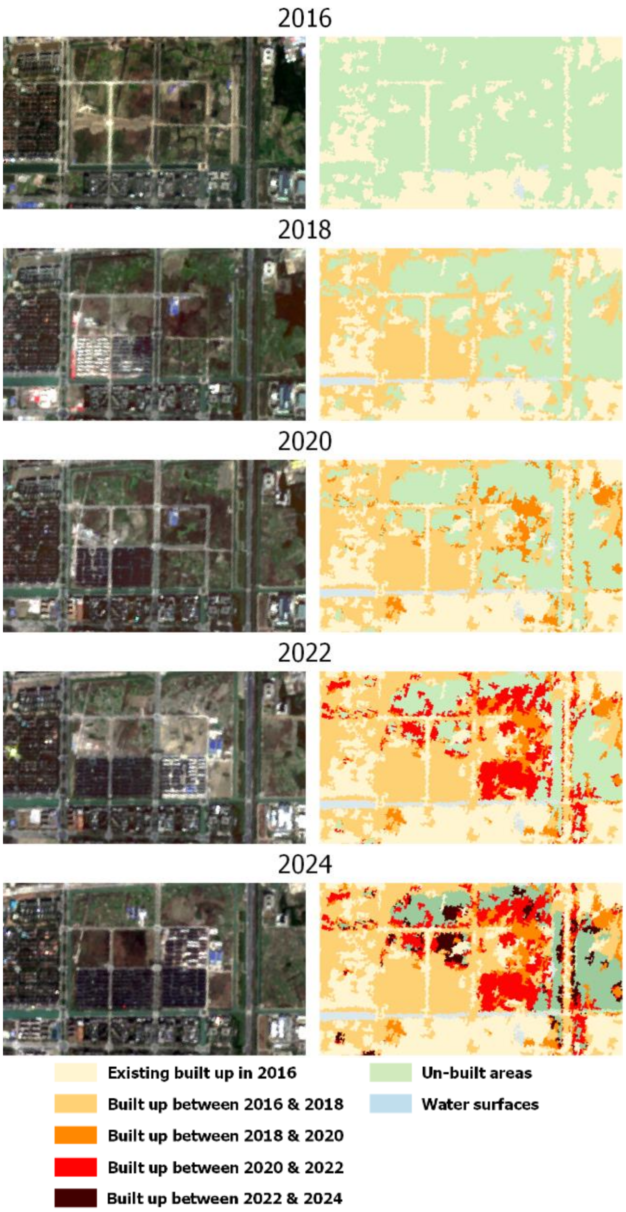

Figure 5. Example of building up process (coordinates 31.111084, 121.489774)

This represent the northern part of Pujiang new town masterplan, and 6 plots are clearly visible. The Random Forest classification method is recognizing in an adequate way the gradual construction of these plots along the years. Of course, the result could be improved, since the images could be affected by different atmospheric condition, slight changes of the vegetation of the empty plots and their temporary land-uses.

The evolution that can be observed represent the most intuitive process of development of the land-use in Shanghai, as well as in other urban areas elsewhere. However, it is interesting to notice that the region of interest is including also areas characterized by the inverse process, hence built-up areas converted into green spaces. We can see an example of this phenomena in figure 6.

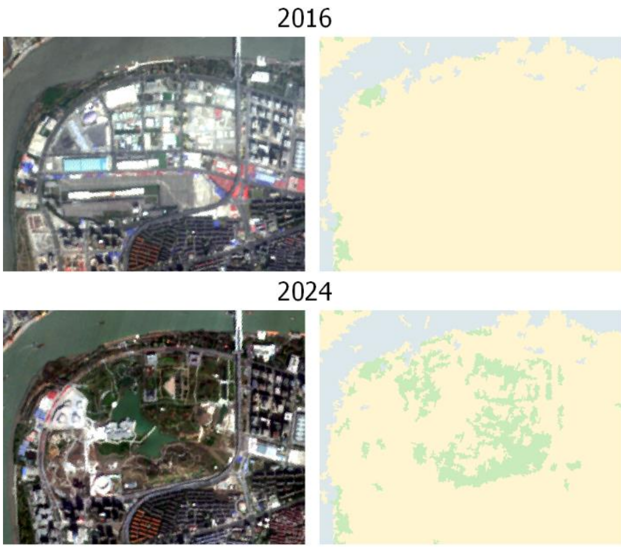

Figure 6. Example of land recovery and conversion into green space
(coordinates 31.181598, 121.472436)

In this case we can observe that in 2016 and the area is completely built-up and there is almost no permeable soil except for a small green area on north-west. In 2024 the whole site is converted into a quite big green area and it got classified accordingly. In this case the classifier did not recognize the water body in the center of it, probably due its artificial origin, hence a different "lakebed" material and depth compared to the one of the river and also a different water composition per se.

4. CONCLUSIONS

Final consideration on the analysed phenomena
We observed that there have been requalification processes that involved the transformation of some built-up areas into unbuilt areas. However, from the change detection analysis reported in figure 7 we understand that this is concerning only the 3% of the total region of interest (class 3.2). Hence, the total surfaces concerning this type of transformation are too few compared to the vastness of the region of interest and the number of areas converted, instead, from green to built-up (16%, class 2.1 from figure 7). Therefore, we can assert, in relation to what was previously stated, that Shanghai has indeed followed a trend predominantly oriented towards urbanization, as expected, albeit with a lower intensity than anticipated.

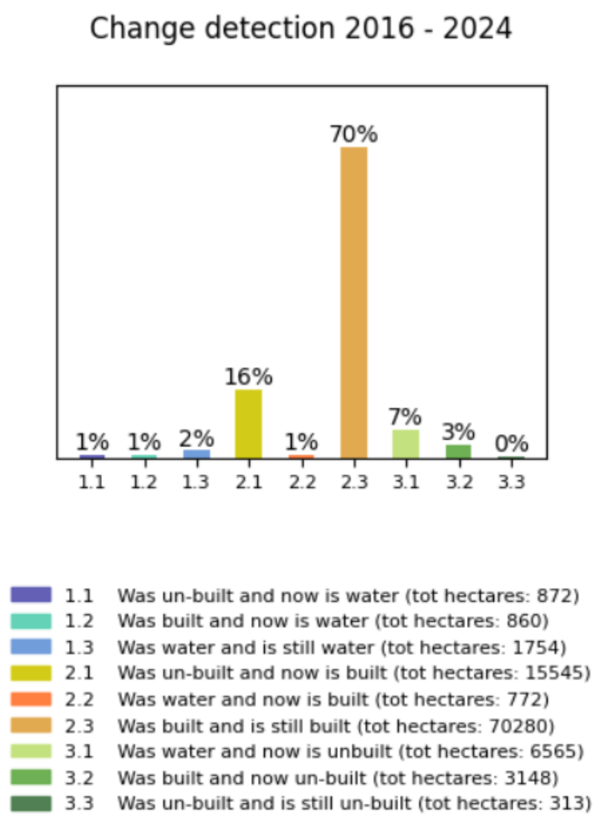

Figure 7. Change detection of pixel classification between 2016 and 2024

The initial question posed in the scope of this paper was to understand whether there were indeed phenomena of conurbation, or whether these did not occur, or whether there were processes of conversion from urbanized to non-urbanized areas.

At the end of this research, we can firmly affirm that the phenomenon of conurbation from 2016 to present days has continued with a constant growing pace, with less intensity than expected, but there has been no change in direction in this regard.

Possible technical improvements and further analysis
Some possible interesting analysis to further refine this research could be:

- Checking the change detection trend on other sample cities both in China and elsewhere to understand possible patterns.
- Comparing these analyses with the output of multispectral indices such as NDBI for the built-up areas, NDBI / SAVI for the non-built-up areas and MNDWI for the water surfaces.
- Training the Random Forest classifier with the output of the multispectral indexes.
- Training the Random Forest classifier with some vector land use databases provided by local authorities (each database being compliant with the year of classification thus representing the situation at that time).
- Comparing this method with a non-supervised classification method.
- Further detection and removal of noises and errors across the whole steps of the analysis in order to have a more reliable picture.

5. REFERENCES

Bissi F., (2018), *Lilong. An historical legacy and an opportunity of development for the future*, Tongji University

Gallo M., (2016), *Shanghai One city nine towns,* La Sapienza

He S., Wu F., (2005), *Property-led redevelopment in post-reform China: a case study of Xintiandi redevelopment project in Shanghai*, Journal of urban affairs, volume 27, number 1, pages 1-23.

Lefebvre A., (2016), *Monitoring Urban Areas with Sentinel-2A Data: Application to the Update of the Copernicus High Resolution Layer Imperviousness Degree,* Clement Atzberger and Prasad S. Thenkabail

Spagnoli L., (2012), *Storia dell'urbanistica moderna,* Vol.2, Zannichelli.

UN HABITAT, NYU (2016), *Atlas of urban expansion,* Lincoln institute of land policies