Extraction of Open Spaces and Identification of Suitable Rooftops for Urban Agriculture: Contribution of Geospatial Technologies for Sustainable Planning

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Abstract

Urbanization represents a major challenge, driving the conversion of agricultural land into high-value uses such as residential, industrial, and commercial developments, largely due to rapid population growth. To address these challenges and enhance urban sustainability, it is essential to incorporate spatial planning strategies that integrate urban and peri-urban agriculture. We consider urban and peri-urban agriculture to be of vital importance in ensuring food security and meeting citizens' needs. Thus, our proposal is based on integrating agriculture into open spaces in urban and peri urban areas, such as community gardens, rooftops and greenhouses. In this way, we will be able to exploit these spaces for the cultivation of agricultural commodities common in the region, such as cereals and market garden crops. This project aims to extract those vacant spaces and rooftops using various methods. For vacant space extraction, three classifiers were used: Support Vector Machine (SVM), Minimum Distance, and Random Forest. With a 75% precision, the SVM classifier had the highest accuracy. For rooftop extraction, three methods were tested, including object-based classification using SVM, the pre-trained and optimized deep learning model Footprint Building Extraction-USA, and Mapflow's building model. According to our analysis, the last two approaches achieved the highest accuracy with F-Factor values above 77%.

Keywords: Satellite Imagery, geospatial technology, Urban agriculture, Vertical farming, Remote Sensing, Machine learning.

1. Introduction

Urbanization is increasing worldwide. Currently, over half of the world's population resides in urban areas. This number is projected to increase to 67% by 2050 (World Bank, 2020). This increase in the urban population is mainly concentrated in metropolitan areas and cities with economic and industrial activities (UN Environment Global, 2019).

In Morocco, the situation is far from exceptional, urban expansion is becoming increasingly alarming and consuming agricultural land. This phenomenon is especially visible in metropolitan cities such as Casablanca (HCP, 2014).
Due to internal migration and rural emigration, the Casablanca region is experiencing extremely rapid population expansion, which raises demand for infrastructure, employment, housing, and services.
According to data from the High Commission for Planning (HCP), the built-up area in the Casablanca-Settat region increased by 77% between 2016 and 2020, rising from 1,259,407 m² in 2016 to 2,234,103 m² in 2020 (HCP, 2023).

This vulnerability can lead to food insecurity issues as the population increases and food demand rises, while agricultural production fluctuates or decreases due to climate change or the conversion of agricultural land to barren or developed land (Aubry et al., 2013).

To address these challenges, many initiatives are promoting sustainable urbanization by encouraging the concept of green and smart cities.

Morocco is implementing strategies and policies aimed at developing sustainable agriculture and mitigating the impacts of urbanization on agricultural production.

Investments in the agricultural sector and innovative solutions for resilient agriculture are being encouraged (Toumi, 2008).

Urban and peri-urban agriculture (UPA) is increasingly recognized as a sustainable solution to address those various socio-economic and environmental challenges. Firstly, it provides a tangible response to food insecurity by enabling local production and direct distribution of fresh food to urban populations, thereby reducing reliance on food imports and enhancing access to a nutritious and balanced diet. Furthermore, UPA can contribute to job creation and the reduction of underemployment by offering employment opportunities in food production, processing, and distribution sectors, as well as in the management of green spaces and community gardens (Pearson et al., 2010).

Geospatial technology plays a key role in this approach by mapping and modeling the open spaces for agriculture.

It identifies optimal locations for installing vertical structures by taking into account sunlight exposure, orientation, and infrastructure (Grard et al., 2018): Plants are classified into different categories according to their light requirements, the cultivation area is located on the ground floor or on the roof of a building, it must be easily accessible to inhabitants and maintenance staff. When choosing the location for the installation, the wind must be taken into account, which can have an influence on plant growth because the plants will tilt and the soil will dry out (gidsduurzamegebouwen,2017).

Identifying suitable rooftops and unoccupied spaces for agricultural installations is the main subject of this study. High-resolution satellite images from Google Earth Pro served as the study's data source.

2. Method

2.1 Study area

Our study area is the metropolitan city of Casablanca, specifically the arrondissement Hay Hassani (Fig1).

Casablanca serves as the economic capital and largest city of the Kingdom of Morocco. It is situated in the central-western part of the country, located along the Atlantic coast at coordinates 33°36′N latitude and 07°36′W longitude. The city is characterized by its population estimated at 3 218 036 residents, encompassing an area of approximately 1,615 square kilometers (RGPH1, 2024). Indeed, agricultural land in this metropolitan city is under heavy pressure, hence the importance of urban and peri-urban agriculture which can help offset the decline in agricultural land by using urban spaces such as rooftops, terraces, balconies and public spaces to grow food.

The region of Casablanca has a Mediterranean climate with an oceanic coastline. The average annual temperature is 17.8°C and the average annual rainfall is around 430 mm (HASSANI et al ,2021).

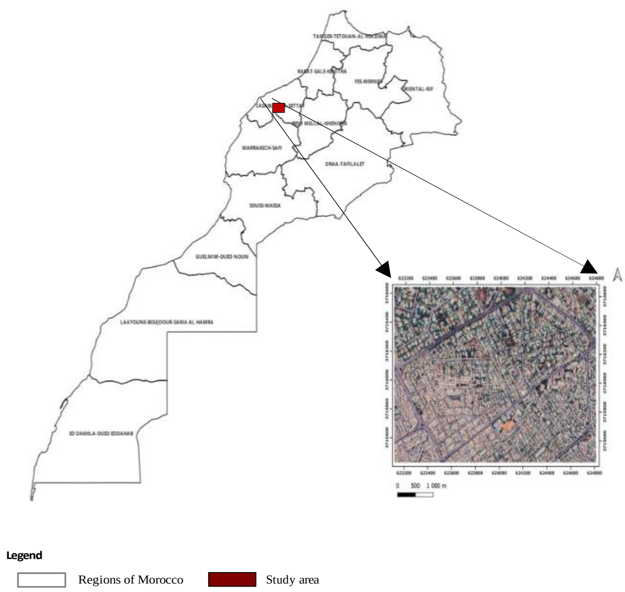

Figure 1 : Study area

El Hanaa district, part of the Hay Hassani arrondissement, occupies a strategically significant geographical position. It lies in the city of Casablanca undergoing rapid economic expansion, with a growing attraction for investment. The presence of the Casa Finance City zone further enhances its role as a central economic hub within the Casablanca-Settat region. Secondly, the population density of the area is high, reaching 11,472 inhabitants per square kilometer. Hay Hassani is also characterized by its diversity of urban uses. There are a variety of zones, including villas, residential, industrial and commercial. This diversity offers opportunities for different types of projects. In view of these factors, Hay Hassani is an ideal and strategic area in which to develop such a projects and initiatives.

2.2 Rooftop Detection

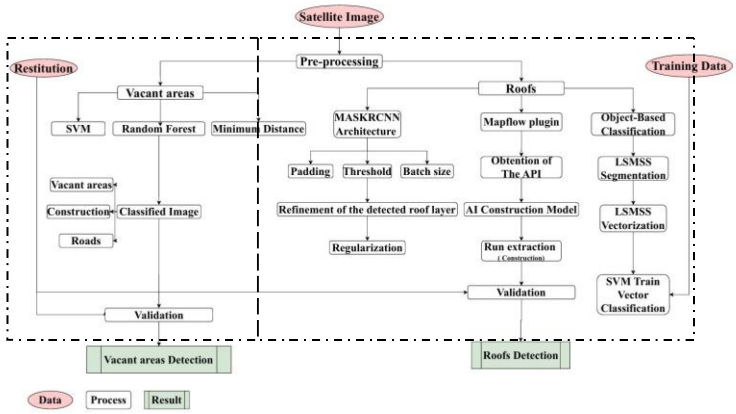

Figure 2: Methodology

The workflow of this step involves automatically extracting rooftop footprints from a satellite image downloaded from the ArcGIS Pro satellite basemap, by adjusting parameters such as spatial resolution, spectral resolution, projection system, image size, and bit depth according to the specific needs of our study.

To perform this automatic extraction, we address the identification of building rooftops using three distinct methods.

The first method relies on deep learning, using the pre-trained and optimized model "Building Footprint Extraction – USA," which is based on the Mask R-CNN architecture within ArcGIS Pro. Next, we apply the Mapflow method in QGIS, also based on deep learning, followed by the use of an object-based classification method.

Finally, to ensure the reliability of these approaches, we carry out a qualitative and quantitative validation of the results obtained from the three methods, allowing for an in-depth evaluation of their effectiveness and accuracy.

2.2.1 MASKRCNN Architecture

This method is based on the pre-trained and optimized deep learning model "Building Footprint Extraction – USA", which automatically digitizes building footprints for each individual rooftop using the Mask R-CNN architecture implemented through the ArcGIS API for Python3 Mask R-CNN focuses on instance segmentation of objects (rooftops), which is a computer vision technique that identifies and separates individual objects in an image by detecting their boundaries and assigning a unique label to each object, treating each as a distinct entity. This is in contrast to semantic segmentation, which aims to extract objects by assigning a single pixel class to all instances of the same type. *(ArcGIS API for Python)*

2.2.2 Mapflow model

Mapflow is a plugin that enables linking and connection to the Mapflow processing API to perform AI feature extraction and add layered output to the QGIS workspace. This plugin is based on AI mapping models using semantic segmentation and other deep learning techniques.

To start processing with this plugin, we selected our (AOI) study area by specifying the existing layer, our satellite image compliant with Mapflow's requirements, and the AI model we used for our case, namely "BUILDINGS".

2.2.3 Object-oriented approach for roof detection

The object-oriented approach consists in processing grouped pixel units rather than individual pixels, using several criteria such as spectral, geometric and contextual information. For our purposes, we have exploited the Orfeo Toolbox plugin with two main steps: segmentation using the Meanshift algorithm and classification using support vector machines (SVM).

After creating a new geometric point vector layer and adding an attribute column named "class", we proceeded to fill this layer with points belonging to two distinct classes: "roof" and "non-roof".

The main objective of SVM is to optimally separate groups of supervised classes, which in our case are “ROOF” and “NON-ROOF”. Using the data from these classes, also known as “support vectors”, the SVM creates an optimized separation hyperplane during the training phase (Maulik,2017).

2.2.4 Validation of roof extraction methods using satellite imagery

The results obtained from the proposed workflow were evaluated through a verification process based on a two-level structure.

2.2.4.1 Qualitative validation

Firstly, at the level of the roof extraction results, we compared the results of the three proposed methods with the cleaned restitution, taking into account several evaluation criteria.
Secondly, we evaluated the segmentation step of the third method by assigning several evaluation factors.

2.2.4.2 Quantitative validation

To assess the quality of predictions, we used several statistical indicators such as:

▪ Recall Index: measures the proportion of total results that are correctly classified;
▪ Precision Index: measures the proportion of correctly identified positive entities;
▪ F-score: derived from the two previous indices, it provides an overall measure of classification performance.

2.3 Vacant Areas Detection

Vacant areas detection involves the use of various data sources and analytical methods such as remote sensing, geographic information systems (GIS), image classification, and machine learning to locate, classify, and analyze land that is not actively built upon or used for infrastructure, agriculture, or other intensive land uses. It is commonly applied in urban planning, sustainable development, agriculture, and land-use monitoring.

2.3.1 Random Forest

The Random Forest algorithm is a supervised classification method that classifies data by constructing multiple decision trees, aiming to improve prediction accuracy. This technique is applied to a test dataset, where several trees are built and their individual outputs are aggregated to determine the final class label. (Shaik et Srinivasan, 2019).

2.3.2 Support vector machine

Support Vector Machine (SVM) is a supervised learning algorithm primarily used for classification tasks. It aims to identify the optimal hyperplane that maximizes the margin between different classes in a linearly separable space. To effectively handle non-linear separability, SVM employs various kernel functions such as the Radial Basis Function (RBF) and polynomial kernels that project data into higher-dimensional spaces. This approach enables robust classification performance, even with limited training samples (Mustafa Abdullah et Mohsin Abdulazeez, 2021).

2.3.3 Minimum distance

This classifier is based on the use of training data to categorize unknown images by measuring proximity within a multidimensional feature space. Each image is assigned to the class to which it is closest — that is, the class that minimizes the distance between the image and the class center in this space. The similarity index is thus represented by this distance: the smaller the distance, the greater the similarity between the image and the class (Jog et Dixit, 2016).

3. Result

3.1 Rooftop Extraction results

3.1.1 MASKRCNN Result

We conducted several tests by adjusting the confidence threshold to achieve roof detection that covers all rooftops with minimal outliers. The table below presents the most representative test among those performed.

	Parameters		Results
Test 1	Padding	128	
	Batch size	4	
	Threshold	0.9	

Test 2	Padding	128	
	Batch size	4	
	Threshold	0.1	
Test 3	Padding	128	
	Batch size	6	
	Threshold	0.6	
Test 4	Padding	128	
	Batch size	6	
	Threshold	0.6	

Table 1: Result of test MASKRCNN Architecture

Finally, to improve the result of the building footprints extracted in test 4, we proceeded to regularize their shapes using the parameters recommended such as right angles. The table below shows the results before and after regularizing the building footprints with the selected parameters.

3.1.2 Mapflow result

A visual inspection of the obtained results revealed several anomalies in the extracted rooftops. In Zone 1, issues related to the orientation of the detected segments were observed. Zones 2 and 3 also exhibited confusion between rooftops and other characteristic urban features. Additionally, the extracted segments consistently displayed a similar rectangular shape. These irregularities may be explained by the nature and composition of the model's training dataset, as well as by the inherent complexity of rooftop geometries in the Moroccan urban context.

Figure 3: Result obtained by applying the "Mapflow" building model with an enlargement of visually detected anomalies.

3.1.3 Object-oriented classification result

After analyzing the results obtained by the Deep Learning and Artificial Intelligence model, we decided to explore object-oriented classification in order to evaluate the performance of these models. To this end, we carried out tests by varying the parameter combinations to perform meanshift segmentation, followed by small-segment fusion and vectorization. We observed that the results obtained were similar, with the detection of roofs in certain parts of the study area using several fragments.

Figure 4: Object-oriented classification result

These results highlight anomalies in roof extraction. We observed that zone 2 and zone 1 had precisely segmented roofs. Zone 3 and Zone 4, on the other hand, showed roofs divided into several fragments. This fragmentation can be attributed to the nature of the roofs present in the actual zone, which is characterized by villas. Villa roofs tend to be fragmented due to the presence of elements such as solar panels, air conditioners, chimneys and other equipment.

3.1.4 Evaluation result

To assess the reliability of the proposed extraction workflow, both quantitative and qualitative evaluations were conducted.

3.1.4.1 Qualitative validation

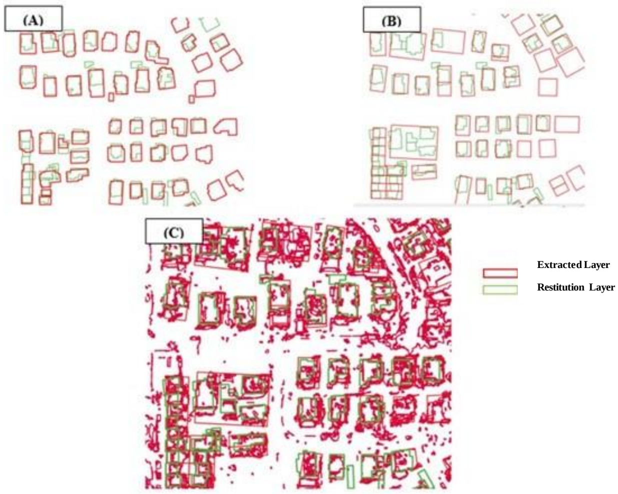

Figure 5: Overlay of the layers of results obtained with the restitution layer. (A) With method 1, (B) With method 2, (C) With method 3.

After a visual evaluation of this overlay, we found that the results of method 1 and method 2 show similar flaws, such as the detection of roofs that do not exist in the restitution, the non-detection of some roofs actually present in the restitution and the grouping of several roofs under the same segment. On the other hand, the results of the third method also show significant aberrations, as mentioned above, despite their ability to correctly detect the location of roofs that actually exist. Consequently, based on this visual comparison, we can conclude that method 3 does not meet the objectives of our study in terms of performance.

3.1.4.2 Quantitative validation

For methods 1 and 2, we carried out quantitative validation by comparing the results with the restitution layer. An area of the El Hana district, comprising 504 roofs from the restitution layer, was selected and superimposed with the results of each method. Next, the parameters (TP, FN and FP) were calculated for each method. The table below presents the results of the calculation of these indices, which allow us to evaluate the performance of each method in terms of roof detection compared to the restitution layer:

	Building footprint MASKRCNN			Mapflow		
	Recall	Precision	F-score	Recall	Precision	F-score
/Nbre of roofs	0.76	0.77	0.77	0.78	0.92	0.85
/Area of roofs	0.83	0.91	0.87	0.77	0.98	0.86

Table 2: Metrics evaluation of method 1 and 2

The results show that method 1 and method 2 perform relatively similarly in terms of roof detection, both as a function of number and roof area, with an F-factor greater 77%.

With regard to accuracy, method 2 shows better accuracy than method 1, whether for the detection of the number or surface area of roofs, with a percentage greater than 92%. This means that 92% of the area and number of roofs detected are actually real.

The selection between the two methods will be determined by the specific objectives of the study and the priorities concerning recall and precision. In our case, where it is essential to accurately detect the area of each existing roof in order to assign an appropriate type of vertical farming project, precision representing the proportion of correctly detected area is of particular importance. Based on this analysis, both methods are valid and suitable for our study.

3.2 Vacant areas Detection

In this study, three distinct machine learning algorithms were employed to classify vacant areas and constructed zones, which are essential for urban land cover mapping. The algorithms selected Minimum Distance, Support Vector Machine (SVM), and Random Forest were chosen based on their ability to handle both spatial features and image-based data, making them suitable for the complexity of urban environments. By using these diverse algorithms, the study aimed to identify which method is most effective at distinguishing between vacant and constructed zones.

The results of the precision analysis highlighted the varying effectiveness of each algorithm in urban classification tasks. The Minimum Distance algorithm achieved a relatively low precision of 67%. This method may be insufficient for complex urban landscapes where the boundaries between land cover types are less distinct. Random Forest algorithm obtained a relatively modest precision of 67%. On the other hand, the SVM algorithm demonstrated the highest precision (75%), which can be attributed to its ability to handle non-linear decision boundaries effectively, making it well-suited for classifying intricate urban environments. These results emphasize the importance of selecting the right algorithm based on the complexity of the classification task and the nature of the urban environment.

Figure 3: Classification results of vacant areas in Elhana district

4. Discussion and Conclusion

Urban agriculture, including vertical farming on rooftops and the use of vacant areas, represents an innovative solution to the challenges of increasing urbanization and the rapid growth of urban environments.

Berger (2013) investigates the potential for rooftop urban agriculture in New York City through a GIS-based spatial analysis. He developed a model publicly accessible datasets to identify buildings with the highest suitability for rooftop farming, including greenhouses and intensive green roofs. The model also evaluates rooftops for their structural capacity to support extensive green roofs with non-agricultural functions. A refined application of the model focuses on the industrial zone of North Brooklyn, situated south of Newtown Creek, revealing over 50 acres of rooftop area suitable for agricultural initiatives. The study aims to promote investment and enhance awareness among the public, policymakers, and stakeholders regarding the opportunities presented by urban agriculture and green roof infrastructure.

A similar initiative aimed at assessing the potential of rooftops for green infrastructure was undertaken by Dominique et al. (2013) in Paris, offering valuable insights into the methodological approaches and urban planning implications. Led by the Parisian Workshop of Urban Planning in collaboration with the Urban Planning Department and the Department of Green Spaces and Environment, the research aimed to support urban planning decisions by establishing a comprehensive inventory and diagnostic of existing green roofs across the city. The study sought to enhance understanding of the current rooftop vegetation stock, address the evolving challenges of rooftop transformations, and identify the potential for expanding green roof coverage. Through the integration of multiple spatial data layers, a qualitative assessment of the rooftops adaptability to green roof systems was carried out. Notably, this work contributed to the city's 2020 Biodiversity Plan, which targeted the creation of 7 hectares of new green roofs. The methodology and findings of this study underscore the importance of geospatial analysis in identifying and promoting rooftop greening opportunities within dense urban environments.

Urban vacant areas such as unused parcels, abandoned spaces, or open lands between buildings represent a valuable opportunity for sustainable urban agriculture. These underutilized spaces can be repurposed to:

- Enhance local food production, especially in densely populated cities with limited arable land.
- Strengthen food security by bringing food sources closer to consumers.
- Promote environmental sustainability through green space creation, stormwater absorption, and improved air quality.

Using rooftops and vacant areas for growing food helps reduce the pressure on limited ground space and supports local food security. However, it can be difficult to choose the right type of crop, as this depends on the season. Evaluating the potential of each rooftop for this kind of agriculture is another important challenge.

Following the extraction of rooftops and vacant spaces, the upcoming phase of the study will involve the integration of several key criteria such as accessibility, solar exposure, and wind conditions in order to determine the most suitable crop types for each rooftop and open space in the urban area.

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