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Identifying impervious surfaces for rainwater harvesting feasibility using unmanned aerial vehicle imagery and machine learning classification

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ABSTRACT

As global demand for clean, reliable water sources continues to increase amid a growing population and the impacts of climate change, effective water conservation and collection methods are more important than ever. Rainwater harvesting has long been a reliable technique for capturing and preserving water, and recent advances in geographic information systems (GIS), unmanned aerial vehicle (UAV) remote sensing, and machine learning (ML) image classification have significantly improved our ability to accurately assess the potential for rainwater harvesting. This study leveraged these technologies to evaluate the feasibility of rainwater harvesting at the Osmanbey Campus of Harran University, using UAV imagery and ML classification techniques to identify suitable surfaces for collection. The results showed that it is possible to irrigate a grass area of 4417 square meters daily for a year using the potential harvested rainwater in the study area, demonstrating the significant potential of rainwater harvesting as a sustainable water source for irrigation purposes.

1. Introduction

Turkey is a water-scarce country, with an average of only approximately 1500 cubic meters of water available per person per year, significantly lower than the global average of around 7000 cubic meters per person per year (Alparslan et al., 2008; Şahin & Manioğlu, 2011; Yiğit et al., 2020). This limited water availability poses a significant challenge for the country and its people, making it essential to prioritize water conservation and collection efforts. Water resource management strategies such as rainwater harvesting can play a key role in addressing this issue and ensuring a sustainable supply of water for the country's needs.

Rainwater harvesting is a widely used technique for collecting and storing water for various purposes, such as irrigation and household use (Boers & Ben-Asher, 1982). With the advancement of Geographic Information Systems (GIS) and remote sensing technologies, methods for assessing rainwater harvesting potential have also evolved. The use of image acquisition techniques, such as Unmanned Aerial Vehicles (UAVs) and Machine Learning (ML) image classification algorithms, has further facilitated this process by providing high-resolution imagery and automating the classification of features relevant to rainwater harvesting. These technologies have made it possible to quickly and accurately assess the potential for rainwater harvesting in various locations, enabling more efficient and effective water resource management.

There have been numerous studies in the literature that have utilized GIS and remote sensing techniques to assess rainwater harvesting potential (Mbilinyi et al., 2007; Mwenge Kahinda et al., 2009; Campisano et al., 2017; Hari et al., 2018; Shokati et al., 2021). Many of these studies have focused on the potential for rainwater harvesting from urban building roofs, but it is important to note that different building complexes may require different methods for assessing rainwater harvesting potential. It is crucial to consider the specific characteristics and needs of each site in order to accurately assess the potential for rainwater harvesting and optimize water resource management strategies. Recent studies have also shown that the combination of UAV images, farm maps, and machine learning can provide a rapid and reliable method for analyzing cultivated areas of crops (Lee et al., 2021). This technique has also been applied at the community level for land classification and mapping using satellite remote sensing and UAV surveying (Meng et al., 2021). Furthermore, the use of optical UAV tilt photogrammetry combined with machine learning algorithms has been demonstrated as a low-cost, high-efficiency, and high-precision method for

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tree species classification (Wang et al., 2021). In addition, a meta-analysis of agro-environmental monitoring studies has shown that the application of machine learning algorithms to UAV imagery produces fast and reliable results (Eskandari et al., 2021). Moreover, when estimating crop above-ground biomass using UAV RGB remote-sensing systems alone, the use of optimized vegetation indices and advanced algorithms such as machine learning technology has been shown to provide high performance (Niu et al., 2021).

This study aims to assess the rainwater harvesting potential of a building complex located in the Harran University Osmanbey Campus using GIS and a combination of UAV imagery and ML classification techniques. In addition to roofs, the potential for rainwater harvesting from marble surfaces on the ground between the building blocks was also considered in the calculation. The results of this study can provide valuable insights for optimizing water resource management strategies and maximizing the potential for rainwater harvesting at this site.

2. Study Area

The study area for this research is a building complex located on the Harran University Osmanbey campus, comprising the Faculty of Engineering and the GAP YENEV (GAP Renewable Energy Research Center) (Figure 1). This complex provides a relevant and representative case study for assessing the potential for rainwater harvesting in urban environments, given its diverse mix of roof and paved surfaces. The results of this study can provide valuable insights for optimizing water resource management strategies and maximizing the potential for rainwater harvesting at this site and similar locations.

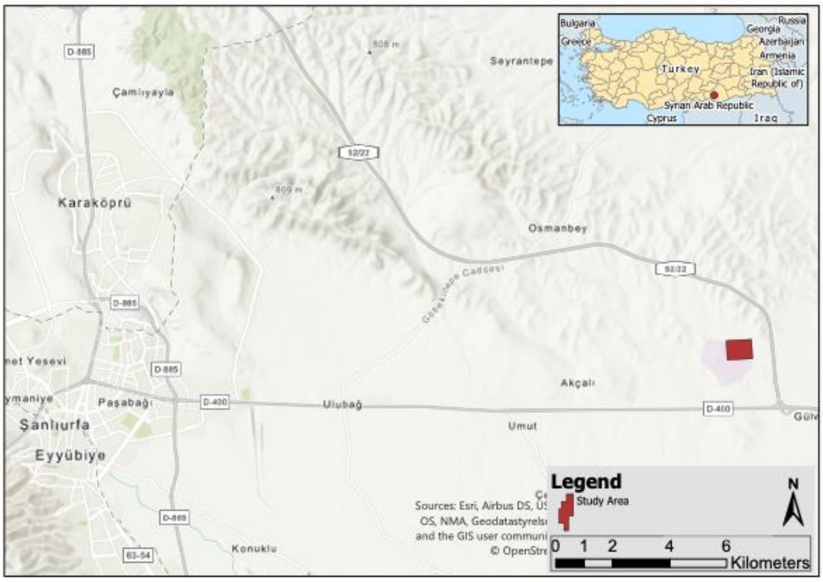

Figure 1. Location of the study area

3. Method

The process of calculating rainwater harvesting potential for various impervious surfaces, such as roofs and paved areas, typically involves several key steps (Figure 2). First, images of the study area are obtained using UAVs. Next, an orthophoto of the study area is generated, which is a georeferenced image that has been corrected for distortions caused by the terrain and the orientation of the camera. ML classification is then performed using predefined parameters to identify and classify different features in the images. The area of each class is calculated, and the rainwater harvesting potential is determined based on the results of the classification and area calculations. These approaches can provide a robust and accurate assessment of the potential for rainwater harvesting and inform the design and optimization of water resource management strategies.

Figure 2. The overall methodology of the study

In this study, images of the study area were acquired using a DJI Mavic 2 Pro UAV at an altitude of 80 meters, with a 70% overlap on both sides. Orthophotos were generated from these images using the Agisoft software package.

To accurately classify the different surface types within the images, this study applied a pixel-based support vector machine (SVM) classification algorithm, a ML technique that has been demonstrated to be efficient and accurate in previous research. SVM is a well-known classification algorithm in machine learning that has been widely applied in various fields including remote sensing image classification. SVM is a supervised learning algorithm that is used for both regression and classification problems. In pixel-based SVM classification, each pixel in an image is considered as an individual sample, and the features extracted from each pixel are used as inputs to train the SVM model. The SVM algorithm then separates the different classes of pixels by constructing a hyperplane in the feature space that maximizes the margin between the classes. The margin is defined as the distance between the hyperplane and the closest samples from each class. The SVM algorithm finds the hyperplane that separates the classes with the largest margin, which is referred to as the maximum margin hyperplane.

In the study, five surface types were identified: soil, green, metal roof, concrete, and marble. While all of these surfaces have different behaviors in terms of rainwater flow, only the metal roof, concrete, and marble classes, which are impervious surfaces, were considered in the calculation of rainwater harvesting potential. The concrete and marble classes were merged due to their similar spectral reflectance and flow coefficient. This approach allowed for a more accurate assessment of the potential for rainwater harvesting in the study area.

The rainwater harvesting potential for both the metal roof and concrete & marble areas was calculated using Equation 1. This equation takes into account the surface area, rainfall intensity, and flow coefficient for each surface type, as well as the desired volume of water to be harvested.

$$rainwater\ harvesting\ potential\ (m^3) = (area \times precip \times coeff \times filter)/1000 \quad (1)$$

The rainwater harvesting potential for each surface type is calculated using Equation 1, which considers the surface area, average annual precipitation, flow coefficient, and filter efficiency coefficient. The surface area is the area of the specific surface type being considered, while the precipitation term represents the average annual rainfall in millimeters for the study area, which is 460.1 mm for the Şanlıurfa region (TSMS, 2022). The flow coefficient represents the ability of the surface to allow rainwater to flow and be collected, and the filter efficiency coefficient accounts for any losses due to filtration. The filter efficiency coefficient, which is defined by German standards in DIN (1989) and has been used in some studies investigating rainwater harvesting potential (Erdoğan, 2002; Yiğit et al., 2020), is typically set to a value of 0.9. The flow coefficients for the various surface types utilized in this study are presented in Table 1.

Table 1. The flow coefficients for surface types (DIN, 1989)

Class	Flow Coefficients
Metal Roof	0.9
Concrete	0.7
Marble	0.7

4. Results

In this study, 172 images were obtained through a carefully planned and executed UAV flight, the details of which are described in the methods section. These images were used to create an orthophoto of the study area, as shown in Figure 3. This orthophoto served as the basis for further analysis and interpretation of the data.

Figure 3. Orthophoto of the study area

Figure 3 displays the layout of the engineering faculty, which includes multiple blocks and a circular building on the left. The ground between the blocks is paved with marble, providing additional opportunities for rainwater collection beyond the roofs of the buildings. To accurately assess the potential for rainwater harvesting, it is necessary to classify the various surfaces within the complex. The design of the faculty, as depicted in the figure, presents opportunities for rainwater collection from a range of sources. Thus, the SVM algorithm, a commonly used ML classification method for geospatial images, was employed. The algorithm parameter for the maximum number of samples was set to 500 per class. The radial basis function (RBF) was used as kernel type to map the input data into a higher-dimensional feature space. An optimal gamma parameter was used in conjunction with the RBF kernel to control the shape of the decision boundary. These parameters were chosen to ensure optimal performance of the SVM algorithm in the classification of the geospatial images. The sample statistics for the training model are presented in Table 2.

Table 2. The train samples statistics

Class	Num. of Samples	Pixels (%)
Green	12	13.23
Soil	11	4.79
Metal Roof	5	16.63
Concrete-Marble	42	65.34

Figure 4 presents the classified image of the study area, divided into four distinct surface types.

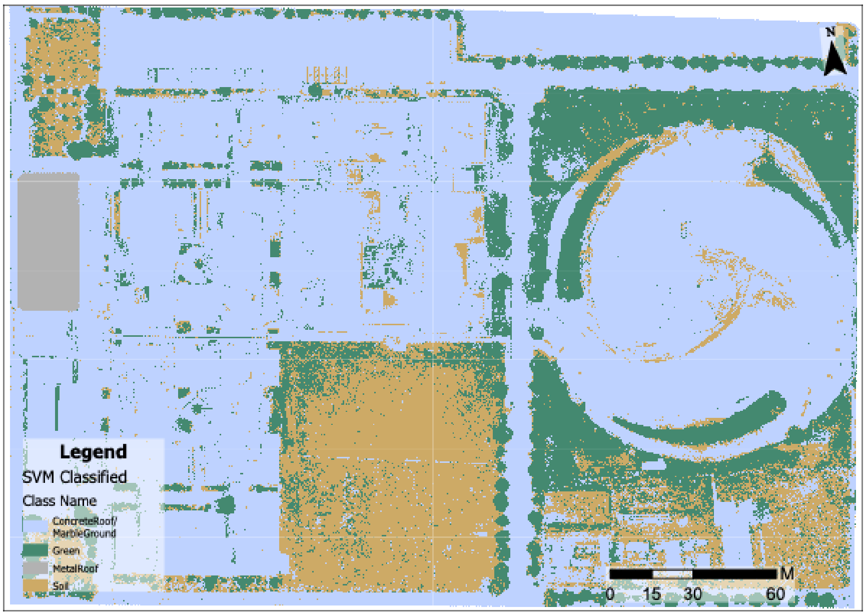

Figure 4. The classified image of the study area

To identify potential areas for rainwater harvesting, it is necessary to calculate the areas of the various surface types present within the study area as impervious and pervious. Using the classified image obtained in this study, the relevant surface types reclassified as impervious, impervious-metal, and pervious (Figure 5).

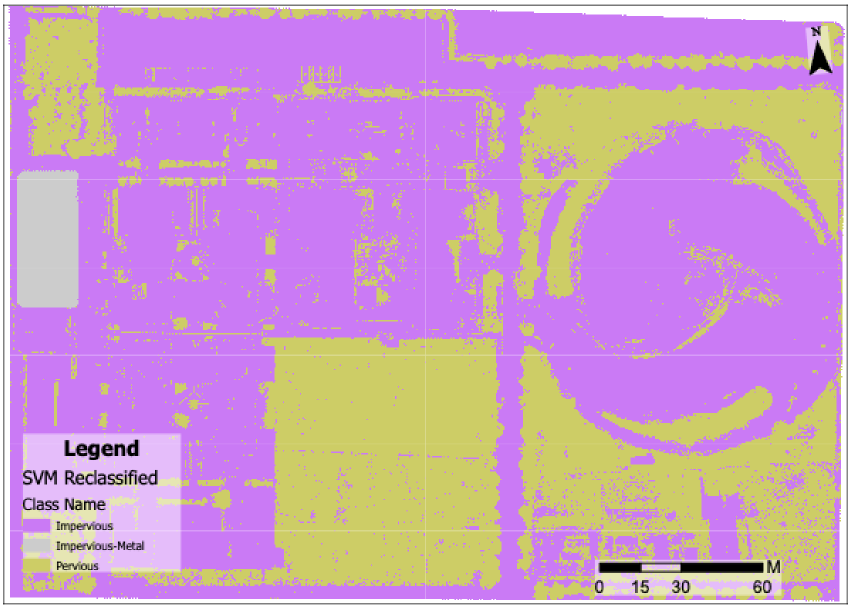

Figure 5. Reclassified image according to the perviousness of the surfaces.

The areas of these surfaces were calculated and presented in Table 3. This information allows for the assessment of the potential for rainwater harvesting within the study area based on the distribution and extent of these impervious and pervious surface types.

Table 3. The area and the ratio of the surface types

Class	Area (m^2)	The ratio of total area (%)
Impervious	41668.55	63.3
Impervious-Metal	1119.06	1.7
Pervious	23039.48	35.0
TOTAL	**65827.09**	**100**

Using Equation 1, the potential for rainwater harvesting was calculated for the concrete & marble and metal roof surface types. The results of this calculation are presented in Table 4. This information allows for the assessment of the feasibility of rainwater harvesting for these specific surface types within the study area.

Table 4. The rainwater potential

Class	Rainwater harvesting Potential (m^3)
Impervious	12078
Impervious-Metal	417
TOTAL	**12495**

It is estimated that a total of 12495 cubic meters of rainwater could potentially be harvested from the study area. By utilizing this water resource, it would be possible to irrigate approximately 4417 square meters of grass daily, based on the average daily water requirement of 7.75 cubic meters per 1000 square meters of grass reported in previous studies (Erdoğan, 2002; Yiğit et al., 2020). This potential for daily irrigation over the course of a year demonstrates the significant benefits of rainwater harvesting in the study area. The results indicate that the amount of water obtained is sufficient for irrigating a significant portion of the green areas surrounding the buildings.

5. Discussion

The images used for classification in this study were acquired in the afternoon, resulting in shadows that may have influenced the classification results. It is important to note that the time of image acquisition can significantly impact the accuracy of classification, with images taken closer to noon likely to have fewer shadows. Future studies should consider the time of flight as an important factor in the acquisition of images for classification purposes.

The SVM algorithm is a popular choice for the ML classification of geospatial images. However, the performance of this algorithm can be influenced by certain parameters, including the kernel type, gamma value and maximum number of samples per class. These parameters can either be set to default values or determined through empirical testing. In this study, various combinations of these parameters were evaluated through visual accuracy comparison, and the optimal settings were selected for use. While the study area in this research was relatively small, the sample size used for training was sufficient to accurately cover the different surface types and could potentially be applied to larger areas with similar success.

The accuracy of the classification method was not formally assessed in this study as the primary aim was to determine the potential for rainwater harvesting. However, a visual accuracy comparison was conducted to ensure the reliability of the results. Besides, the metal roof area, which can be measured with relatively higher accuracy compared to other areas, was measured and compared in the orthophoto and classified image. The result showed an accuracy of percentage99. Although this value is not valid for the whole area, it is an indication that this method performs a near-perfect classification for easily distinguishable objects. While it is generally advisable to include formal accuracy assessment in research, the specific goals of this study and the relatively small size of the study area made a visual comparison sufficient for the calculation of rainwater harvesting potential.

The collection and storage of rainwater on marble surfaces may present unique challenges compared to building roofs. To address these challenges and facilitate the accurate planning of rainwater storage systems, high-resolution digital elevation models derived from UAV imagery can be used to identify runoff directions and accumulation patterns on marble surfaces. This information is essential for the effective design and implementation of rainwater storage systems on marble floors.

The combination of ML and UAV techniques with GIS provides fast and effective solutions for identifying rainwater harvesting potential, thereby rendering them applicable in this area of study

6. Conclusion

The present study employed a UAV flight to gather high-resolution images of a building complex, which were subsequently used to create an orthophoto of the study area. Through the application of the SVM algorithm, the orthophoto was classified to identify the various surface types within the complex. By analyzing the classified image, the impervious surfaces, including building roofs and ground marble areas, were quantified and used to calculate the potential for rainwater harvesting within the complex. This methodology demonstrates the usefulness of combining UAV imagery and ML techniques in evaluating the feasibility of rainwater harvesting and similar applications.

Although there are numerous studies involving ML and UAV techniques, their application for assessing rainwater harvesting potential is still rare, especially with regards to ground surfaces adjacent to the roof area. Therefore, the combination of these techniques with GIS represents a promising approach to accurately estimate rainwater harvesting potential and should be further explored in future research.

The combination of UAV imagery and ML algorithms allows for rapid assessment of various applications, including the determination of rainwater harvesting potential. Additionally, this method can be utilized in a range of other applications, such as the installation of solar panels on roofs, monitoring of landscapes, and detection of land use and land cover. The use of ML in the classification of UAV imagery offers a versatile and efficient solution for these and other endeavors.

Author Contributions

The study was carried out by a single author.

Statement of Conflicts of Interest

There is no conflict of interest.

Statement of Research and Publication Ethics

Research and publication ethics were complied with in the study.

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