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Research paper

Mapping of impervious surfaces with the use of remote sensing imagery: Support Vector Machines classification and GIS-based approach

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Abstract: This study focuses on the problem of mapping impervious surfaces in urban areas and aims to use remote sensing data and orthophotos to accurately classify and map these surfaces. Impervious surface indices and green space assessments are widely used in land use and urban planning to evaluate the urban environment. Local governments also rely on impervious surface mapping to calculate stormwater fees and effectively manage stormwater runoff. However, accurately determining the size of impervious surfaces is a significant challenge. This study proposes the use of the Support Vector Machines (SVM) method, a pattern recognition approach that is increasingly used in solving engineering problems, to classify impervious surfaces. The research results demonstrate the effectiveness of the SVM method in accurately estimating impervious surfaces, as evidenced by a high overall accuracy of over 90% (indicated by the Cohen's Kappa coefficient). A case study of the "Parkowo-Leśne" housing estate in Warsaw, which covers an area of 200,000 m², shows the successful application of the method. In practice, the remote sensing imagery and SVM method allowed accurate calculation of the area of the surface classes studied. The permeable surface represented about 67.4% of the total complex and the impervious surface corresponded to the remaining 32.6%. These results have implications for stormwater management, pollutant control, flood control, emergency management, and the establishment of stormwater fees for individual properties. The use of remote sensing data and the SVM method provides a valuable approach for mapping impervious surfaces and improving urban land use management.

Keywords: classification, impervious surface, support vector machines (SVM), remote sensing, geographic information system (GIS), Land Use/Land Cover (LULC), ArcGIS, machine learning

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1. Introduction

Mapping of impervious surface is used in the management of construction projects and their production can serve a number of objectives. Examples of their use include the implementation of flood protection measures as part of emergency management, the establishment of standards for the management of pollutants associated with stormwater runoffs, but they can also be used in the determination of stormwater runoff charges at the level of individual plots (properties) or as a proxy approach in the determination/verification of the relationship between green areas and bioactive areas. The latter point is sufficiently regulated in Polish law. Researchers point out that accurate calculations of the percentage of impervious surface for a given catchment area or at the plot level (for the purposes of Low Impact Developments) are needed to manage stormwater more effectively in large cities like Warsaw [1]. However, the technical problem in estimating impervious area is often the size of the study area, which makes it difficult to collect appropriate data. For relatively small areas, mapping such surfaces is of course not a major problem, as it can be based on accurate aerial photographs. Applying such a method to larger areas can be time-consuming and costly, but as always in such situations, technology comes to the rescue. More specifically, estimating the impervious area of medium-sized surfaces (such as the area of one of the Warsaw housing estates studied in this article, which reaches just under one million square metres) can be done using appropriate high-resolution remote-sensing aerial imagery containing the near-infrared band. It is worth noting that the near-infrared band is characterised by a sufficiently high reflectance to allow such images to easily map vegetation that is representative of pervious surfaces. One way to represent pervious surfaces very well is to use the Normalised Difference Vegetation Index (NDVI), which represents visible light relative to near-infrared light [2]. Vegetation (and therefore permeable surfaces) can be represented by high NDVI values. On the other hand, built-up areas (impervious surfaces) such as concrete structures (building structures), pavements or roads or car parks have NDVI values in the sub-zero range (zero should be considered as the value that separates vegetation production /pervious surfaces/ from impervious surfaces).

The classic methods for estimating impervious surfaces are, of course, detailed soil/ ground surveys in the field with the use of GPS, but these are very time-consuming and expensive [3]. Alternatives include digitisation of paper maps and feature extraction using appropriate algorithms, and surveys using remote sensing imagery. Studies using high-resolution remote sensing imagery to detect changes at large geographic scales are well suited for quantifying the extent of impervious surfaces [4]. In particular, satellite and remote sensing imagery are suitable for mapping large areas and studying their changes over time (so-called subtle urban dynamics), while at the same time they are not very time-consuming to produce, making such studies cost-effective. The seriousness of the problem posed by impervious surfaces is such that they bring together a whole spectrum of different professionals, including engineers, planners, architects, but also scientific researchers [5]. It is also important to highlight the proliferation of Geographic Information System (GIS) platforms that facilitate land cover studies (including those related to impervious surfaces), and that integrate different methods to facilitate the classification of such surfaces, e.g. by implementing different machine learning methods. One of these methods is Support

Vector Machines (SVM), which is characterised by its high classification performance and versatility in solving a wide range of engineering problems, and which has been validated in previous studies in various knowledge domains. Sobieraj et al. (2022) [6] point out that SVM is one of the scientific methods that can be useful for calculating the percentage of impervious surfaces or for land use/land cover (LULC) classification in urban environmental studies.

In a nutshell, the motivation for the research experiment that is the subject of this article is manifold. It should be noted that image classification and impervious surface estimation is one of the most important issues in civil engineering, including urban and spatial planning and, as mentioned above, issues related to the water cycle of construction sites, including environmental assessment, water quality, determination of stormwater charges, environmental management issues. As there is a lack of this type of research, this work aims to fill a gap. Mapping and spatial and temporal analysis of impervious surfaces are critical when viewed through the lens of land use planning policy and environmental protection and land use management [7]. It is also worth mentioning that the classification results depend on the choice of appropriate classification algorithms (SVM, is one of them, however, there are many more) and on the accuracy of the remote sensing data, which are crucial as they form the basis for the models [8]. In this study, we analyse an area of about one million square metres, which depicts the "Parkowo-Leśne" housing estate in Warsaw. In order to adequately perform this type of study, high-resolution remote sensing imagery is required, as the accuracy of such imagery affects the accuracy of the results (more precisely, the accuracy of the classification measured by Cohen's kappa coefficient [9]). For this purpose, orthophotos with an infrared channel and a suitable pixel size (1 px = 25 cm) were used in the study. These orthophotos were imported from the Geoportal service, which provides the main map resources available in Poland. The data used for this study is from May 2017. The surface mapping itself was carried out using the GIS software (ArcGIS). More precisely, the remote sensing materials made available on the geoportal are optical aerial images containing the infrared band.

In the next section of the article, the SVM research method (with special attention to the versatility of the method in applications from different fields, especially in solving engineering problems) and the GIS-based remote sensing, on which the classification of impervious surfaces is based, are explained in more detail. Section 4 presents the results, while Section 5 provides a broader discussion of the results and knowledge about classification, the SVM method and impervious surfaces (including a review of the prior studies). The article concludes with a section on conclusions.

2. Methods and materials

2.1. REA of the study and remote sensing data

This article deals with the area of the "Parkowo-Leśne" housing estate (about one million square metres in size), located in the north-western part of Warsaw on Obrońców Tobruku Street in the immediate vicinity of Fort Bema – a beautiful park with ruins of the fort [10]. Geographically, the housing complex is located on the edge of the Vistula basin and Bemowo Forest (52°14′–16′ N and 20°55′–57′ E) [see Figs. 1 and 2].

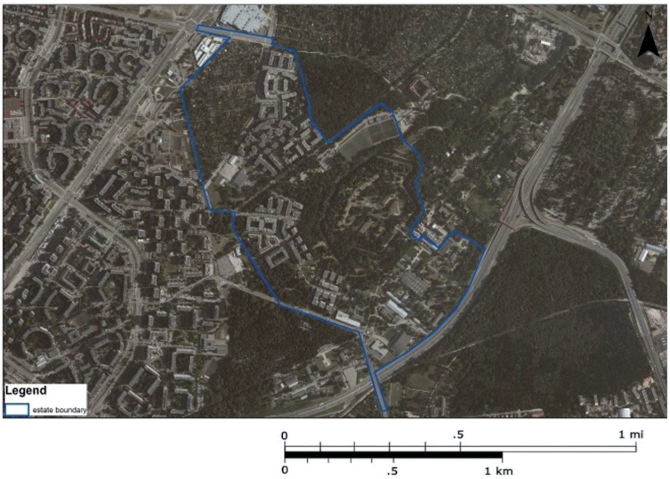

Fig. 1. Location of the investigated "Parkowo-Leśne" settlement complex – aerial view of the settlement [source: own elaboration]

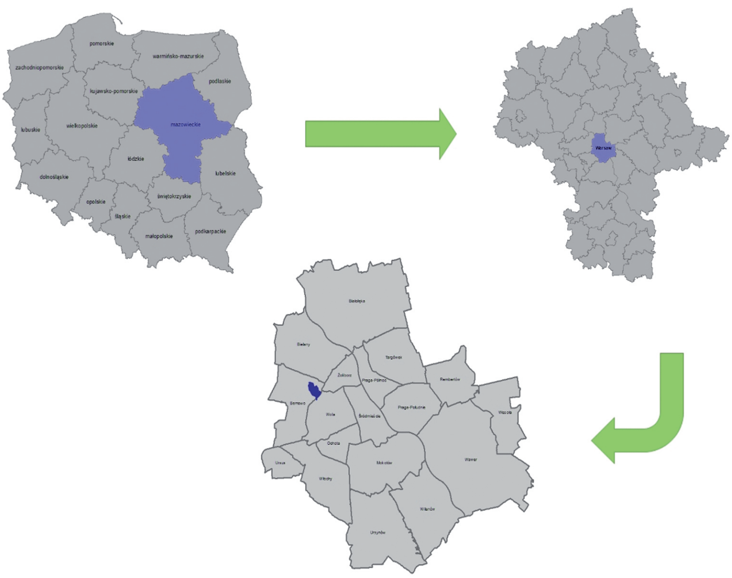

Fig. 2. Location in relation to the province and the municipality in territorial terms (Poland ≥ Mazowieckie Voivodeship ≥ Warsaw County) [source: own elaboration]

The construction of the "Parkowo-Leśne" housing complex was completed in 2009. The flats in this housing complex are one of the pearls on Warsaw's map of residential buildings. The buildings are furnished to a high standard, some of them have large terraces or gardens bordering the park itself, so that residents can feel at home right next to the forest. The buildings have between 4 and 6 floors and there are many small shops and service businesses in the settlement.

The choice of the “Parkowo-Leśne” housing complex for mapping impervious surfaces is not accidental. The study area and its land characteristics adequately take into account the problem of spectral heterogeneity, i.e. it is heterogeneous in terms of different object categories and land covers [11]. Such heterogeneity further complicates the study involving a partitioning of land cover, including impervious surfaces, and poses a major challenge. On the other hand, a good result shows the effectiveness of the classification method used, i.e. the SVM. In fact, only pixel shuffling is a true test of the survey method used and the underlying remote sensing data (imagery). It therefore makes sense that the surveyed area includes tall trees, parks, water bodies (river, pond, etc.), but also multi-storey buildings, local access roads, car parks, shops, playgrounds, etc. – and the area under study includes all these features. In addition, it has already been demonstrated that the importance (severity) of the different subcategories of impervious surfaces varies. For example, it has been shown that the negative impacts of roofs – when viewed through the prism of hydrological impacts – are smaller compared to roads and transport infrastructure [12]. In order to adequately perform this type of study, high-resolution remote sensing imagery is required, as the accuracy of this type of imagery is reflected in the results (or more precisely, in the classification precision measured by the Cohen’s Kappa coefficient). For this purpose, the study uses orthophotos with an infrared channel and a suitable pixel size (1 px = 25 cm) [see Fig. 3].

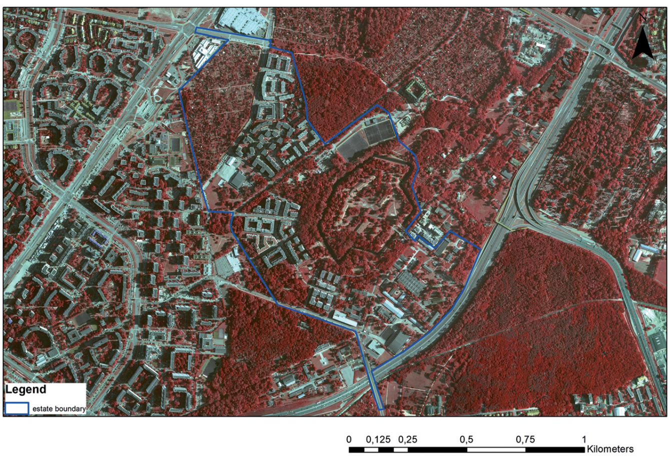

Fig. 3. Orthophotomap with infrared channel (“Parkowo-Leśne” housing estate complex)

These orthophotomaps were imported from the Geoportal service (geoportal.gov.pl), which provides the main map resources available in Poland. The data used for this study is from May 2017. More precisely, the remote sensing materials provided on the Geoportal are optical aerial images containing the infrared band. The surface mapping itself was carried out using the software ArcGIS 2.9.

2.2. Support vector machines

2.2.1. Support Vector Machines as a method applied in solving classification problems

Support Vector Machine (SVM) is a supervised learning algorithm used for classification and regression analysis. It was first proposed by Vapnik and Cortes in 1995 [13]. SVM is a powerful tool for image classification because it is able to find the best separating hyperplane that maximizes the distance between different classes. SVM is widely used in impervious surface and land use/land cover (LULC) mapping because it can handle large datasets and complex features [14].

Mapping impervious surfaces with SVM involves classifying land surfaces into pervious and impervious categories. Impervious surfaces include roads, buildings, and other structures that do not allow water to penetrate the soil. Classification of impervious surfaces is important for urban planning, environmental monitoring, and flood control. SVM can handle high-dimensional and nonlinear data, making it suitable for mapping impervious surfaces.

Similarly, SVM is also used in LULC mapping. LULC mapping involves classifying land into different categories such as forest, grassland, urban areas, and water bodies. SVM is an effective tool for LULC mapping because it can handle large datasets and complex features. More specifically, it can handle multi-class classification problems and is therefore suitable for LULC mapping [15]. Mathematically, SVM is a linear binary classifier that finds the best separating hyperplane between different classes. Given a set of training samples $\mathbf{x}_i, y_i$, where $\mathbf{x}_i$ is the i-th feature vector and y_i is the corresponding class label, SVM finds the hyperplane that maximizes the margin between the two classes. The hyperplane is defined by the equation:

$$\mathbf{w}^T\mathbf{x} + b = 0 \tag{2.1}$$

where $\mathbf{w}$ is the weight vector to the hyperplane, $\mathbf{x}$ is the input vector, and b is the bias term. The distance between the hyperplane and the nearest sample from each class is called the margin, and SVM finds the hyperplane that maximizes the margin.

The decision function of SVM is given by:

$$f(\mathbf{x}) = \mathrm{sign}\left(\mathbf{w}^T\mathbf{x} + b\right) \tag{2.2}$$

where sign is the sign function that returns –1 or +1 depending on the sign of the argument. In other words, we are looking for the weight vector w and the bias term b that maximize the margin, which can be approached as a solution to the following optimization problem: minimize $\frac{1}{2}\|w\|^2$, under the condition $y_i(w^T x_i + b) \geq 1$ for all i, where y_i is the class label of the i-th data point. This optimization problem can be solved using Lagrange multipliers.

This leads to a dual problem involving only inner products between the input vectors. The solution to this problem gives us the weight vector w. To make predictions for new data points, we simply evaluate $f(x)$ and classify the data point based on the sign of $f(x)$.

It is also worth noting that SVM can be extended to handle non-linear data by using kernel functions that map the data to a higher-dimensional feature space where a linear classifier can be used. The most commonly used kernel functions are the linear kernel, the polynomial kernel, and the radial basis function (RBF) kernel.

In summary, SVM is a powerful tool for image classification, especially for mapping impervious surfaces and LULC. SVM can handle large datasets and complex features, and can be extended to handle non-linear data using kernel functions. It has been widely used in remote sensing and GIS applications for impervious surface mapping and LULC, and is expected to continue to play an important role in these fields.

2.2.2. Impervious surfaces and LULC studies

It is worth emphasising the need to build a proper knowledge of impervious surfaces in relation to urban drainage solutions, such as environmentally sustainable development (i.e. bioretention gardens, green roofs, bioswales, etc.), as well as the need for a more sustainable approach to urban drainage. Mrowiec et al. (2021) [16] argue that impervious surfaces in urban areas can have adverse effects on the health of streams and worsen water quality, resulting in reduced habitat quality. Therefore, it is important to build a proper knowledge of impervious surfaces in relation to urban drainage solutions, such as environmentally sustainable development, including bioretention gardens, green roofs, bioswales, etc. The current development of urban drainage systems is shaped to maintain the natural hydrology cycle by using the site layout and integrated control measures. Natural hydrology refers to practices and systems that use natural processes, including infiltration, evapotranspiration, and retention to keep the site's water balance of predevelopment conditions. See Table 1 for a summary of important work related to building knowledge on impervious surfaces and land cover.

The research results presented in Table 1 indicate, among other things, a linear segmentation model based on contextual information and considering texture or reflective properties. This was one of the first studies to address urban coverage classification through remote sensing [17]. At that time, remote sensing was not as widespread as it is today. However, it required adequate development of computing power and suitable sensors to make this research method popular. In the early years of the development of research combining segmentation with remote sensing, it was based on classical estimation, i.e. the land cover, or more precisely the spectral mixture, was modelled. For example, a regression model [4] or a regression tree model [19] was used to estimate the amount of impervious surface. It was not until the field evolved that more advanced methods such as decision trees [21] were used. Furthermore, it was only with the advent of high-resolution imagery that segmentation using hierarchical image segmentation [22] or feature extraction methods based on morphological attribute profiles [23] or normalised multitemporal analyses of parts of impervious surfaces [10] became possible. Other methods for studying impervious surfaces include cross-source analysis of multisensory data [7]. In the last decade, increasing

Table 1. A review of the literature with regards to impervious surfaces and LULC studies

Authors/Year	Contribution
Møller-Jensen (1990) [17]	Expert approach and development of a classification methodology for Landsat-TM satellite imagery for urban coverage. A linear segmentation model revealing texture, contextual information and reflectance properties.
Sawaya et al. (2003) [18]	A mapping and classification of impervious surfaces and lake water clarity, and aquatic vegetation.
Yang et al. (2003) [19]	Investigation of urban impervious surfaces as a continuous variable based on a regression tree model and Landsat-7 ETM+ datasets and high-resolution multisensor and multisource imagery.
Wu and Murray (2003) [20]	Traditional estimation methods: a linear spectral mixture model for modeling heterogeneous urban land cover.
Lu and Weng (2006) [21]	A new approach to urban land use classification based on the combined use of impervious surface and population density. Classification of urban impervious surfaces with the decision tree method using a linear spectral mixture analysis model.
Li et al. (2010) [22]	Application of an object-oriented method for mapping urban impervious surfaces using high resolution imagery. Hierarchical image segmentation method combining multichannel watershed transformation and watershed contour dynamics.
Mura et al. (2010) [23]	Morphological attribute profiles (MAPs) as a tool for spatial feature extraction from remote sensing imagery.
Wang et al. (2022) [24]	Estimating impervious surfaces in urban areas by integrating linear spectral mixture analysis (LSMA) with regression analysis. LSMA alone lacks sensitivity to pixel brightness, resulting in variability of endmembers and difficulties in distinguishing similar spectral features. To address this, a spectral angle mapping (SAM) based regression analysis model is introduced, which accurately estimates non-impervious and high-impervious surface densities but is less accurate for low/medium-density impervious surfaces.
Lu and Liu (2012) [25]	An assessment of the opportunities and challenges associated with the increasing availability of various location data collection technologies for geospatial research, with particular emphasis on three aspects, namely bulk location data collection, bulk location data analysis, and location data pattern recognition.
Liu et al. (2013) [26]	An integration of the different data sources and the creation of the modified normalized difference index of impervious surface.
Arsanjani et al. (2013) [27]	Integration of remote sensing features with social knowledge (VGI, OSM data, etc.).
Liu et al. (2015) [28]	A conceptual linkage of social sensorimotor and remote sensing and a consideration of the significant problems associated with the application of social sensorimotor data and associated analytics.

Continued on next page

Table 1 – *Continued from previous page*

Authors/Year	Contribution
Johnson and Iizuka (2016) [29]	Land use and land cover classification (LULC) using Landsat imagery and OSM data.
Hu et al. (2016) [30]	Classification of land according to different land use classes using data extracted from Open Street Map (OSM) and various features derived from Points of Interest (POI) data, as well as data obtained from Landsat 8 Operational Land Imager (OLI) imagery.
Huang et al. (2017) [31]	A multi-level approach (pixel, grid and city block) to urban change analysis.
Zhang and Huang (2018) [32]	A multi-object approach to monitoring surface changes over several years. The extraction of impervious surfaces from high-resolution images.
Yu et al. (2018) [33]	An approach to impervious surface estimation based on integration of remote sensing data and social data.

Source: own elaboration.

amounts of site data have been used and attempts have been made to search for specific patterns in these data [25]. The ease and volume of available data, e.g. point-of-interest data (POI), has become a challenge for increasingly sophisticated sensing methods, including artificial intelligence and machine learning algorithms [30]. In recent years, social data-based research has become prevalent, including studies that have used some remote sensing features alongside social knowledge [33]. Multi-level and multi-object approaches have also become indispensable in studies of land cover [32] and the subtle dynamics of urban change.

2.2.3. The use of GIS-based analysis in solving engineering problems

The development of remote sensing technologies and the increasing availability of high-resolution imagery as well as suitable software for processing and analysing such data contribute to the growing popularity of this type of study. In some cases, unfavourable environmental factors – more specifically, spatial variability and difficult specificity of land cover – make it difficult to conduct this type of research and assess environmental conditions in a conventional way. Zawadzki et al. (2020) [34] refer to orthophoto maps and emphasise the advantages of their use as they reflect remote sensing data and, in particular, enable coverage of relatively large areas if they have adequate spatial, spectral, radiometric and temporal resolution. D'Emilio et al. (2018) [35] point out that orthophotos in the modern world provide knowledge on very different topics, e.g. ecological, but also geophysical, geochemical, biological or even social.

Therefore, in such cases, a suitable survey method is needed that is both cost-effective and allows for rapid results – which is particularly important. A prerequisite is, of course, that the results have a sufficiently small error to allow a reliable assessment and to draw relevant conclusions. GIS Methods based on remote sensing and geostatistics are well suited to process data for relatively large areas, allow reliable results to be obtained quickly and are cost-effective [36]. Remote sensing data processing provides a solid basis for validating collected satellite and aerial imagery (one of the earliest forms of remote sensing) for scientific conclusions based on geostatistical and quantitative methods. Scientists are increasingly using remote sensing data for their research. The analysis of orthophotos (remote sensing images with relatively high resolution) is used in various fields, such as digital elevation model, estimation of environmental changes, or crop production [37].

3. Results

In this study, a binary classification (for impervious and pervious surfaces) was carried out based on an appropriate grouping of the selected classes according to LULC (more precisely 7 classes: bare soil, grassland, roofs and pavements (paving), artificial surfaces, paved (asphalt) roads, forest (trees) and water bodies). The classification results were obtained using the software GIS (ArcGIS 2.9). A visualisation of the classification of the 2 classes: impervious and pervious surfaces can be found in Fig. 4.

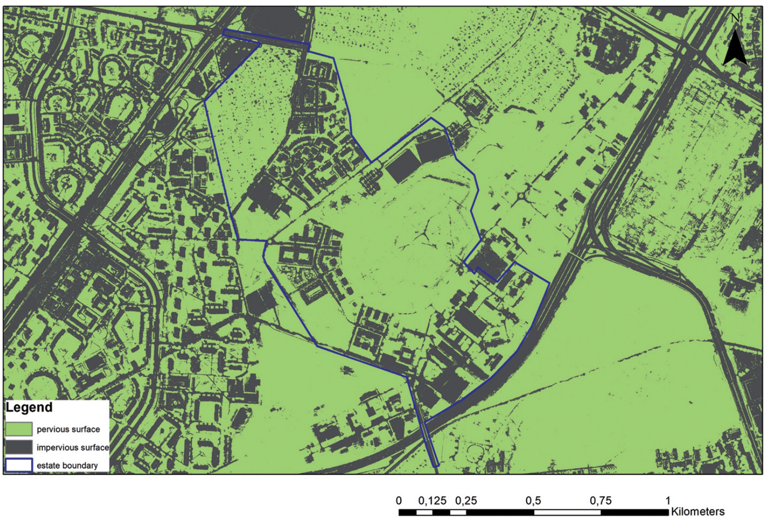

Fig. 4. Results of the classification (mapping) of impervious surfaces with the SVM method [source: own elaboration in ArcGIS 2.9]

The accuracy of the classification can be assessed on the basis of the confusion matrix shown in Table 2.

According to the results in Table 2, the Cohen's Kappa index was 0.9151, so it can be assumed that the classification of the seven different classes gave satisfactory results.

Table 2. Confussion Matrix with use of the SVM method

Class Value	Pervious surface	Impervious surface	Total	U_Accuracy	Kappa
Pervious surface	63	4	67	0.940	0
Impervious surface	1	51	52	0.980	0
Total	64	55	119	0	0
P_Accuracy	0.984	0.927	0	0.957	0
Kappa	0	0	0	0	0.915

Source: own elaboration in ArcGIS 2.9.

A different way to represent pervious surfaces is to use the NDVI (mentioned earlier), which represents visible light relative to near-infrared light. Vegetation can be represented by high NDVI values. On the other hand, built-up areas (pervious surfaces) such as concrete structures (building structures), pavements or roads or car parks have NDVI values in the sub- zero range (zero should be considered as the value that separates vegetation production /pervious surfaces/ from impervious surfaces. The use of NDVI provides the opportunity to classify areas according to different index ranges (i.e. below and above zero) so that the study area can be divided into vegetation (representing pervious surfaces) and non-vegetation (representing impervious surfaces). The results of such segmentation are shown in Fig. 5. It should be noted, however, that this method underestimates the actual results, especially for tall objects, as some areas may be shaded because they obstruct light propagation and in

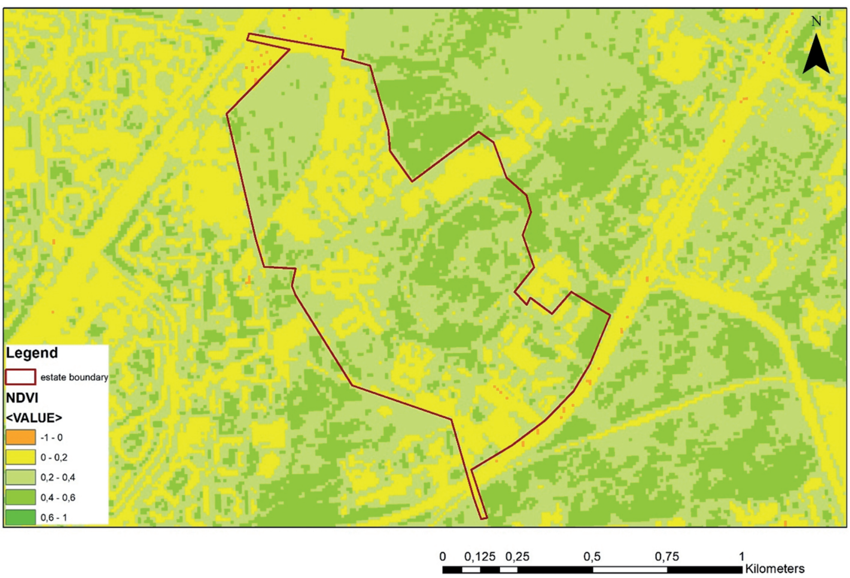

Fig. 5. Visualisation of impervious surfaces based on NDVI

this case may be detected as opaque. Conversely, some areas without vegetation, e.g. soils, may be incorrectly detected as opaque even though they are permeable surfaces. To avoid such errors, the classification based on the GIS platform was carried out in a supervised manner, which allows manual corrections in such cases.

The method presented in this study also served to calculate the area of the impervious/pervious classes studied. The calculation of the classified impervious and pervious areas was carried out with the software GIS (i.e. ArcGIS 2.9). Separate rasters (grids) were created for each area by selecting specific areas (extracted by attributes). The flowing rasters (grids) were then converted to integer rasters (using raster calculator function) and the area of each grid was calculated as a table using zonal statistics. As it turned out, the pervious area for the studied estate complex is equal to 630 118 m^2 (about 67.4% of the total complex) and the impervious area 304 538 m^2 (corresponding to the remaining 32.6%).

4. Discussion

In the empirical experiment, the "Parkowo-Leśne" settlement in Warsaw, with an area of about one million square meters, was investigated to gain a comprehensive understanding of the land cover and impervious surfaces. The classification of the area was performed using the machine learning method Support Vector Machines (SVM). SVM is a non-parametric machine learning method based on optimization that is widely used in prediction and classification to solve complex engineering problems. Numerous studies have demonstrated the superiority of SVM in remote sensing applications, including classification of SAR images [38]. Compared to other classifiers, such as the ML classifier, SVM classifiers are not only faster, but also exhibit better processing capabilities with greater feature support and faster processing of training data [39]. However, it is important to note that SVM classifiers are more complex than their counterparts despite their superior performance. Nevertheless, SVM is characterized by its generalization, i.e., it can accurately interpret the absence of certain features. SVM minimizes the structural risk and boundary of generalization error rather than training error [40]. Moreover, SVM classifiers can handle bitmaps of different resolutions and depths, making them suitable for segmentation using appropriate training attribute patterns and subsequent pixel-based classification. Suitable training attribute patterns are used for segmentation and the classification itself is performed on the pixels. Fig. 6 shows the training patterns for impervious surface classification for the residential complex (settlement) "Parkowo-Leśne" studied in this article.

The results of this study demonstrate the effectiveness of using remote sensing data and near-infrared orthophotos with a resolution of 1 px = 0.25 m for accurate classification and mapping of impervious surfaces. The Support Vector Machines method yielded a remarkable overall accuracy of over 90% in estimating impervious surfaces, as shown by the Cohen's Kappa coefficient. This accuracy was influenced by the use of high-resolution imagery, where each pixel corresponded to a size of 25 cm for actual objects, as opposed to typical satellite imagery with pixel sizes of 10-25 m. The high Cohen's Kappa values obtained in this study inspire confidence in the accuracy of the results obtained.

Fig. 6. Training sample for the classification of impervious surfaces for the “Parkowo-Leśne” housing estate complex

The contribution of this study extends the existing literature and confirms the growing importance of remote sensing in solving civil engineering problems. Comprehensive knowledge of impervious surfaces, which include building roofs, roads, parking lots, sidewalks, and other concrete structures, is critical due to their impact on the water cycle, urbanization, pollution, and environmental sustainability [41]. Detailed maps and classifications of impervious surfaces are necessary to effectively address these issues.

Various geodetic methods, including remote sensing, are used to map impervious surfaces. Remote sensing, known for its cost-effectiveness, plays an important role in this regard [42]. However, to achieve accurate classification, suitable remote sensing images with high resolution are required. Such precise data enable the monitoring of subtle urban dynamics [32]. However, overcoming the challenge of spectral heterogeneity, especially the mixing of impervious surfaces with vegetation, requires a suitable segmentation method. This challenge can be overcome by using high-resolution imagery and efficient classification techniques such as SVM [26].

Impervious surfaces play a crucial role in monitoring dynamic changes in urban land cover and analyzing interactions at the human-environment interface [20]. One notable change involves hydrologic issues that are influenced by the spatial arrangement and size of impervious surfaces. Large impervious surfaces contribute to increased runoff during storm events and impede groundwater recharge [6]. The creation of impervious surfaces in urban areas leads to frequent flooding, localized inundation, climate change, and pollutant transport disruption [1].

The study presented in this paper extends the existing research by combining remote sensing, a GIS method, with one of the most efficient machine learning algorithms, SVM. The study confirms the high efficiency of combining these methods in classifying impervious surfaces and urban land use. The proposed methods have wide applicability in civil engineering projects to solve prediction and classification problems.

In addition, it is important to emphasize the importance of accurately characterizing impervious surfaces in urban environments. Accurate identification and mapping of impervious surfaces is an important foundation for urban planning, stormwater management, and environmental assessments. Knowledge of the distribution of impervious surfaces helps to evaluate the impacts of urbanization on hydrologic processes, water quality, and overall environmental sustainability. It also enables assessment of human activities and changes in the urban landscape, which facilitates informed decision making in land use planning and urban ecosystem analysis. The integration of remote sensing techniques, such as high-resolution imagery and advanced classification algorithms like SVM, provides a robust framework for gathering detailed and up-to-date information on impervious surfaces, paving the way for comprehensive urban management strategies and informed policy actions.

The results of this study have significant implications for several areas, including urban planning, environmental management, and infrastructure development. Accurate mapping and classification of impervious surfaces using remote sensing and SVM techniques offers valuable insights for designing sustainable cities. The ability to quantify impervious surfaces and their spatial distribution helps optimize stormwater management strategies, mitigate flood risks, and improve water resource planning. Accurate identification of impervious surfaces also supports pollution control efforts by targeting areas with high pollutant generation potential. In addition, detailed knowledge of impervious surface dynamics facilitates effective land use planning, optimization of land use patterns, and preservation of green space. These insights can inform decision-making processes and help policymakers, urban planners, and engineers develop resilient cities that balance the environmental sustainability, resource efficiency, and human well-being. Finally, the integration of remote sensing and machine learning techniques demonstrated in this study opens up avenues for further research and application, and promotes the use of advanced technologies in urban management practices to address current challenges and promote sustainable urban development.

5. Conclusions

In this paper, we show the most efficient method for classifying impervious surfaces (i.e. SVM). The study uses a platform GIS, in which suitable digital image processing algorithms and machine learning methods have been implemented, which has greatly facilitated the performance of the corresponding classification and mapping of impervious surfaces. Such platforms are very suitable for visualising the results of land cover classification, including impervious surfaces, and are inexpensive. They can also be used to combine different methods (such as the NDVI index method presented in this study, which can be used as a proxy measure for mapping impervious surfaces).

This paper analyses the results of the classification of an urban settlement in one of the districts of Warsaw (the settlement complex "Parkowo-Leśne" with an area of one million square metres). The study was conducted using orthophotos (with infrared channel) with a resolution of 0.25 m and classification using the SVM method. As an alternative method, impervious surfaces were also visualised based on the NDVI index, which has a high positive correlation with vegetation (and can be considered a proxy for pervious surfaces). The study also examined important work on impervious surfaces, remote sensing and the SVM method. Both this overview and the results of the experiment conducted enable the building and consolidation of knowledge on impervious surfaces, which in turn can support real-world applications such as construction projects. The increasing availability of remote sensing data (provided on the Geoportal in Poland) and especially the availability of high-resolution orthophotos (where 1 px corresponds to 25 centimetres of actual dimensions) create significant challenges and opportunities for applications in construction. Also important for this type of research is the popularisation of the GIS platforms, in which numerous functions have been implemented to perform practical calculations, e.g. the size of appropriately classified surfaces. This article shows how a combination of remote sensing and the SVM classification method can be used in mapping impervious surfaces. In summary, the SVM classifier has achieved a very high overall accuracy of more than 90 per cent in estimating impervious surfaces, which is evident from the confusion matrix and in particular the Coehan's Kappa index. This confirms the high level of detail of a properly performed classification based on the relevant image types (i.e. orotophoto maps), the SVM method and the selection of appropriate training sets. In practise, it was possible to accurately calculate the area of the surface classes studied. It turned out that the pervious area is 630 118 m^2 (about 67.4% of the total complex) and the impervious area is 304 538 m^2 (which corresponds to the remaining 32.6%).

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Wizualizacja powierzchni nieprzepuszczalnych z wykorzystaniem zdjęć teledetekcyjnych: klasyfikacja support vector machines i podejście oparte na GIS

Słowa kluczowe: klasyfikacja, powierzchnie nieprzepuszczalne, maszyny wektorów nośnych (SVM), teledetekcja, system informacji geograficznej (GIS), Land Use/Land Cover (LULC), ArcGIS, uczenie maszynowe

Streszczenie:

Niniejsze badanie koncentruje się na problemie wyznaczania powierzchni nieprzepuszczalnych na obszarach miejskich i ma na celu wykorzystanie danych teledetekcyjnych i ortofotomap do dokładnej klasyfikacji i wizualizacji tych powierzchni. Wskaźniki powierzchni nieprzepuszczalnych i oceny terenów zielonych są szeroko stosowane w planowaniu przestrzennym i urbanistycznym do oceny środowiska miejskiego. Władze lokalne polegają również na oszacowaniu wielkości powierzchni nieprzepuszczalnych w celu obliczania opłat za wodę deszczową i skutecznego zarządzania odpływem wody deszczowej. Jednak dokładne określenie wielkości nieprzepuszczalnych powierzchni jest poważnym wyzwaniem. W niniejszym badaniu zaproponowano wykorzystanie metody Support Vector Machines (SVM), podejścia opartego na rozpoznawaniu wzorców, które jest coraz częściej stosowane w rozwiązywaniu problemów inżynieryjnych, do klasyfikacji powierzchni nieprzepuszczalnych. Wyniki badań pokazują skuteczność metody SVM w dokładnym szacowaniu powierzchni nieprzepuszczalnych, o czym świadczy wysoka ogólna precyzja wynosząca ponad 90% (na co wskazuje współczynnik Kappa Cohena). Studium przypadku osiedla „Parkowo-Leśne” w Warszawie o powierzchni 200 000 m^2 pokazuje skuteczne zastosowanie metody. Wyniki wskazują, że powierzchnie przepuszczalne stanowiły około 67,4% całego kompleksu, podczas gdy powierzchnie nieprzepuszczalne stanowiły pozostałe 32,6%. Wyniki te mogą mieć wpływ na zarządzanie wodami opadowymi, kontrolę zanieczyszczeń, zapobieganie powodziom, zarządzanie kryzysowe i ustalanie opłat za wodę opadową dla poszczególnych nieruchomości. Wykorzystanie danych teledetekcyjnych i metody SVM zapewnia cenne podejście do wizualizacji powierzchni nieprzepuszczalnych i poprawy zarządzania użytkowaniem gruntów miejskich.

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