Identification of asbestos-cement roofing with the use of remote sensing data in the capital city of Poland

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Abstract

Asbestos, a group of fibrous minerals prized for its strength, flexibility, and resistance to chemicals, heat, and electricity, was widely used in industrial applications, reaching its peak in the 1960s and 1970s with over 3,000 uses. Today, asbestos-cement roofs account for more than 80% of current asbestos-containing products. The International Agency for Research on Cancer has classified asbestos as a carcinogen, and the World Health Organization has called for global efforts to regulate and eliminate carcinogens, including asbestos, in both occupational and environmental exposure. Convolutional Neural Networks and high-resolution orthophotomaps were examined for the dense urban areas, i.e. the capital city of Poland, Warsaw. The area of Warsaw is divided into 18 districts. Two classes were distinguished: buildings with asbestos-cement roofs ("asbestos") and buildings with other roof coverings ("non-asbestos"). Orthophotomaps, developed in 2021 based on aerial imagery with a spatial resolution of 5 cm and three spectral channels (RGB) were used. The overall accuracies (OA) over 90% were obtained. Differences in overall accuracy resulting from the size of the image signature were insignificant and amounted to up to 2 percentage points. The highest producer's accuracies for the asbestos roofing class were obtained for a window of 128 by 128 pixels, while for the other roofing similar results were obtained for patterns with window sizes of 128 by 128 and 96 by 96 pixels. As a result of the research, the amount of asbestos-cement roofs was estimated, and their spatial location was determined in surveyed districts of the capital city of Warsaw. These results indicate that it is possible to train a neural network and, using available remote sensing data, estimate the scale of the phenomenon even in dense urban areas. Establishing a universally applicable technique would facilitate large-scale asbestos monitoring and management, thereby contributing to improved public health and safety across the EU.

1. Introduction

Asbestos refers to a group of naturally occurring hydrated ferro-magnesium aluminium silicates. These include chrysotile and amphibole asbestos. Chrysotile asbestos is characterized by high elasticity, relatively short fibres, ease of weaving, resistance to high temperatures and abrasion, low thermal and electrical conductivity, and poor chemical resistance. In contrast, amphibole asbestos is resistant to acids and alkalis but exhibits low elasticity, less propensity for weaving, and sensitivity to high temperatures (Ross et al., 2008).

The industrial use of asbestos began with the development of methods to reinforce cement products with asbestos fibres (Hendry, 1965). Asbestos production peaked in the 1960s and 1970s, with asbestos being incorporated into over 3,000 products worldwide (Virta, 2006). More than 90% of global asbestos production consisted of chrysotile, primarily used in the asbestos-cement industry for the manufacture of roofing materials and pipes. Chrysotile was also used in textiles, electrical wires, insulation, friction materials, yarns, paper, household items, and numerous other products (Frank and Joshi, 2014).

The initial documentation of asbestos's pathogenic effects emerged in the medical literature during the 1930s (Murray, 1990). The deleterious impact of asbestos on human health is primarily attributed to the inhalation of airborne asbestos fibres. These fibres accumulate in the lungs over an individual's lifetime, and the extent of their harmful effects is contingent upon the number of fibres retained in the lower respiratory tract and the depth of their penetration into lung tissue (Jamrozik et al., 2011). According to the World Health Organization, respirable fibres with diameters less than 3 micrometres and lengths exceeding 5 micrometres are implicated in the development of neoplasms (WHO, 1986). Furthermore, asbestos has been designated as a carcinogen by the International Agency for Research on Cancer, a specialized cancer agency of the World Health Organization (IARC, 1977).

Owing to the deleterious effects of asbestos on human health, numerous countries have implemented measures to restrict or eliminate its use in production. Within the European Economic Community, the prohibition of trade and use of chrysotile asbestos was enacted through Council Directive 76/769/EEC, issued on July 27, 1976. This directive aimed to harmonize the laws, regulations, and administrative provisions of Member States concerning restrictions on the marketing and use of certain hazardous substances and preparations (Council Directive, 1976). These regulations became effective on January 1, 2005 (Commission Directive, 1999). The European Union has emphasized the critical goal of completely removing all utilized asbestos and asbestos-containing products (EESC Opinion, 2015). Despite this ban, substantial quantities of asbestos remain in existing buildings, and not all Member States have established records of the locations and quantities of asbestos-containing materials requiring disposal. Consequently, there is an insufficient baseline for accurately estimating the amount of asbestos still in use in Europe, hindering effective risk management. Asbestos-cement roofing remains the most prevalent asbestos-containing product globally, accounting for over 80% of current use (Collegium Ramazzini Statement, 2010).

Considering the necessity to eliminate asbestos from the environment and prevent asbestos-related diseases, the World Health Organization (WHO) and the International Labour Organization (ILO) have recommended the development of National Asbestos Profiles as part of programs aimed at eradicating asbestos-related diseases. These National Asbestos

Profiles should include comprehensive data on historical asbestos imports, disaggregated by year and type of asbestos, imports of asbestos-containing products categorized by type and year, as well as historical data on the production of asbestos and asbestos-containing products, detailed by year, type of asbestos, and type of product. The WHO has emphasized that all countries should implement programs to control and eliminate carcinogens, including asbestos, in both occupational and environmental settings. The cessation of asbestos use in production has been identified as a critical intervention area for reducing environmental exposure to carcinogens (WHO, 2007). National policies should be developed and enforced to address this issue. For cross-country comparisons, data from the United States Geological Survey (USGS) is frequently utilized, as it compiles annual information on asbestos extraction and fibre production by country (Virta, 2006). These data are used to develop indicators of asbestos consumption in production. Furthermore, Commission Directive 1999/77/EC, issued on July 26, 1999, mandates that the marketing and use of asbestos-containing products should be subjected to the strictest possible restrictions. It also highlights that an effective method of protecting human health is to prohibit the use of chrysotile asbestos fibres and products containing them.

Studies and attempts to estimate the amount of asbestos used in production or the quantity of asbestos-cement products still in use are being conducted. However, these efforts typically focus on small areas, often near factories or plants that historically used asbestos in their production processes. Such studies have been carried out for locations including among others Casale Monferrato in Italy (Magnani et al., 2001), Glasgow in the United Kingdom (De Vos Irvine et al., 1993), and Wittenoom in Australia (Musk et al., 2008). The classification of asbestos-cement roofs in two communes (Chęciny and Baranów) in Poland achieved satisfactory results using convolutional neural networks (CNNs). This classification was conducted on aerial imagery in both RGB and CIR compositions, using image signatures to train the CNN and validate the classification outcomes. The overall accuracy of detecting asbestos-cement roofs was over 89% (Krowczynska et al., 2020; Raczko et al., 2022).

Due to the significant public health risks associated with inhaling asbestos fibres, it is crucial to invest in methodologies aimed at estimating the quantity of this mineral in urban environments, where exposure levels are higher (Krowczynska and Wilk, 2023). This study aims to demonstrate the feasibility of identifying asbestos-cement roofs using high-resolution aerial imagery with a spatial resolution of 5 cm and convolutional neural networks (CNNs) in the capital city of Poland, Warsaw. This research was motivated by the need to explore potential solutions for mapping and quantifying asbestos roofing and to develop a practical, reliable operational method, also for use in densely built-up urban areas using orthophotomaps with higher resolution compared to previous studies.

2. Materials and methods

2.1 Study area

Warsaw, the capital and largest city of Poland, is situated in the east-central part of the country along the Vistula River. Covering an area of approximately 517 square kilometres, Warsaw is home to a population of around 1.8 million residents. The city serves as a major political, economic, and cultural hub, with a metropolitan area that extends significantly beyond its administrative boundaries, hosting over 3 million inhabitants. Warsaw is divided into 18 administrative districts. In. the undertaken survey Wawer and Wesoła District were surveyed (Figure 1).

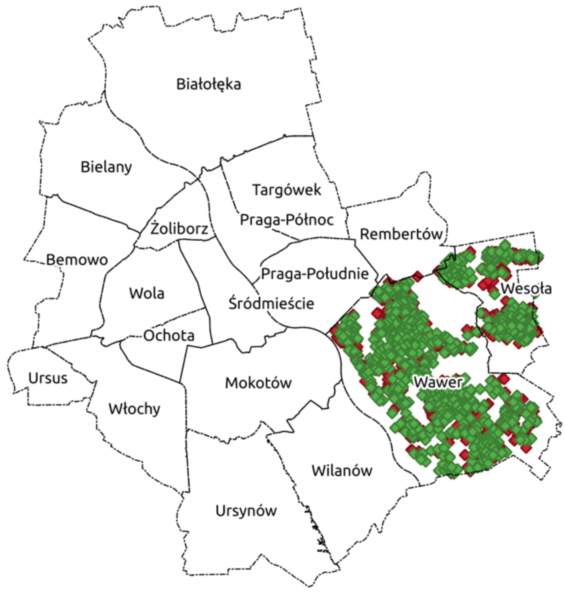

Figure 1. Study area.

2.2 Data gathering

High-resolution aerial imagery with a spatial resolution of 5 cm and three spectral channels (RGB), developed in 2021 was derived from the Central Office of Geodesy and Cartography of Poland. Primary data were obtained from in-situ surveys and field visits. During fieldwork, data on localization, asbestos or non-asbestos cement roofs, the urgency of removal, and the function of the building were collected. The study utilized data provided by the Central Office of Geodesy and Cartography, which includes information on buildings' identifiers, geometry, and type according to the Classification of Fixed Assets. This classification encompasses various categories such as transportation and communication buildings, commercial and service buildings, office buildings, educational, scientific, and cultural buildings, as well as sports facilities, other non-residential buildings, and residential buildings. These data were used to conduct analyses based on building functionalities, to later develop potential funding strategies for the removal of asbestos-cement roofs.

Additionally, an effective method of identifying asbestos-cement roofs would enable cyclical updating of asbestos-cement roof inspections, which is currently difficult to do due to the high cost of fieldwork.

2.3 Data preparation and processing

To train the artificial neural networks, it is essential to construct a sufficiently representative dataset that describes the distinct classes. In the inventory work, two classes were identified: buildings with asbestos-cement roofs (class "asbestos") and buildings with other types of roofing (class "non-asbestos"). Each building was assigned a location point at its central part. The analysis employed newly created location points due to discrepancies between the building outlines obtained from land and property records and the actual shape and location of the buildings as observed in the aerial imagery (Figure 2).

Figure 2. Location points for generating image signatures (red - "asbestos", green - "non-asbestos").

To ensure that the number of observations in each class was comparable, a random sampling method was employed for observations from the "non-asbestos" class (Figure 3). Specifically, from a total of 797 buildings in the Wawer and Wesoła districts identified as "non-asbestos," a random sample was selected to match the number of observations in the "asbestos" class, which comprised 953 buildings. This approach aimed to create a balanced dataset for training and validating the convolutional neural network (CNN), ensuring that the classes were represented equally in the analysis. Reference data points from the asbestos-cement roofs database were utilized to prepare image signatures for training the CNN and for performing classification validation. Each image signature is a window centred on each vector layer point, with a dimension of 27x27 to 128x128 pixels and encompassing data from three spectral bands. Each image signature was annotated with a label to classify it into one of the predefined classes.

Figure 3a. Examples of "asbestos" image signatures with different window sizes.

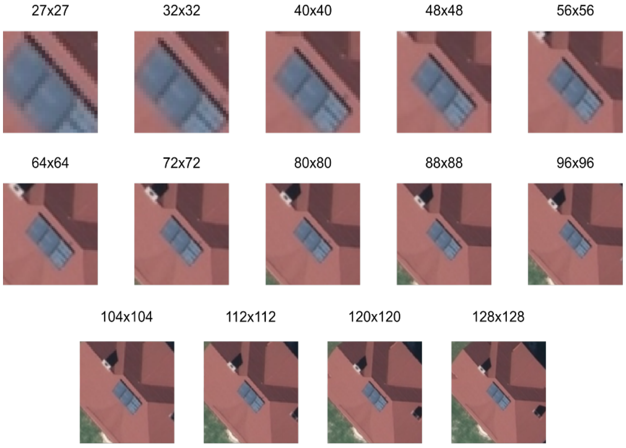

Figure 3b. Examples of "non-asbestos" image signatures with different window sizes.

A novel aspect of the research involves testing fourteen variants of image pattern sizes while maintaining the spatial resolution of the imagery. The results are presented for the four windows with the highest classification accuracy in sizes 47 by 47 pixels, 64 by 64 pixels, 96 by 96 pixels and 128 by 128 pixels (Figure 4).

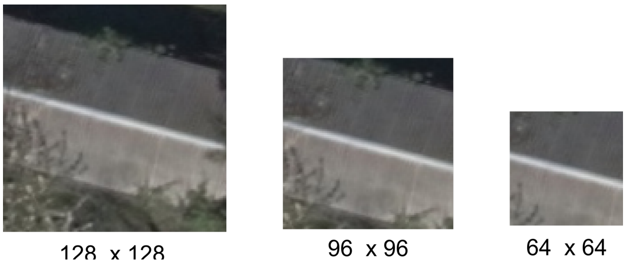

Figure 4. Different sizes of image signature.

A convolutional neural network (CNN) with inception modules was employed in this study. Specifically, the CNN developed by Krowczyńska et al. (2020) and tested in new areas by Raczko et al. (2022) was used to investigate the feasibility of identifying asbestos-cement roofs in two districts of Warsaw. Before the training, the collected image patterns were divided into two subsets using stratified sampling. Two-thirds of the image patterns were allocated for training, while the remaining one-third was reserved for validation. The use of inception modules, which facilitate multi-scale feature extraction by applying convolutional filters of varying sizes within a single layer, enhances the network's ability to capture complex patterns and improve classification performance.

Convolutional neural network architecture was as follows (Krowczynska et al., 2020; Raczko et al., 2022):

1. a convolutional block consisted of:
   - convolutional layer (64 kernels, 3 × 3 kernel, stride 1
   - activation layer (ReLU activation function)
   - batch normalization layer
   - four feature extraction blocks, each followed by a pooling layer and spatial dropout layer (dropout rate 0.55)
2. Two fully connected blocks consisting of:
   - fully connected layer (1024 neurons, ReLU activation function)
   - batch normalization layer
   - activation layer (ReLU activation function)
   - dropout layer (rate = 0.50)

- output layer (softmax function).

The network was trained over 128 epochs with a batch size of 64 samples. The learning rate was configured at 0.0015, and the Adam optimizer was employed throughout the training process. The binary cross-entropy loss function was utilized to evaluate and minimize errors during the network training.

The network training was conducted using the TensorFlow (Abadi et al., 2023) and R-Keras libraries (Cholet, 2015) within the R programming environment (R Core Team, 2023).

The qualitative assessment of the classification results was performed using a confusion matrix. The confusion matrix provided information on which buildings (signatures with labels) were classified into the "asbestos roof" class and which were classified into the "non-asbestos roof" class.

3. Results

Results obtained from the conducted experiments underwent a comprehensive accuracy assessment. This evaluation involved a detailed analysis of the classification performance, where metrics such as producer accuracy (PA), user accuracy (UA) and overall accuracy (OA) were calculated to gauge the effectiveness of the model. Additionally, the confusion matrix was used to provide insights into the classification distribution, indicating which buildings (signatures with labels) were accurately classified as having asbestos roofs and which were correctly identified as having non-asbestos roofs. This thorough accuracy assessment ensured the reliability and validity of the experimental outcomes.

window size scenario	asbestos roofs		non-asbestos roofs		overall accuracy
	PA	UA	PA	UA	
128 pixels	91.52	93.37	96.65	93.66	93.80
96 pixels	88.13	95.70	97.47	92.59	93.47
64 pixels	91.11	93.27	93.85	93.82	93.01
47 pixels	91.27	92.22	91.15	93.10	91.93

Table 1. Accuracy metrics for the classification scenarios concerning different window sizes.

Differences in overall accuracy resulting from the size of the image signature were insignificant and amounted to up to 2 percentage points. The highest producer's accuracies for the asbestos roofing class were obtained for a window of 128 by 128 pixels, while for the other roofing similar results were obtained for image signatures with window sizes of 64 by 64 and 96 by 96 pixels.

Figure 4. Classification results in Wawer District (asbestos-cement roofs identified in red, other roofs identified in green).

As a result of the research, the number of asbestos-cement roofs was estimated, and their spatial location was determined in surveyed districts of the capital city. It was estimated that the Wawer district contains 886 metric tons (Mg) of asbestos-cement roofing sheets used as building coverings, while the Wesoła district contains 309 metric tons (Mg). These results indicate that it is possible to train a neural network and, using available remote sensing data, estimate the scale of the phenomenon even in dense urban areas.

4. Discussion

The identification of asbestos cement roofs and the determination of their quantity and distribution across various public administrative units are crucial for the process of removing these carcinogenic materials. Research efforts employ a range of methods and typically focus on relatively small areas (Krowczynska et al., 2020). Accurate mapping and identification are essential for effective planning and execution of removal programs, ensuring public health and compliance with environmental regulations (Wilk and Krowczynska, 2021). Further studies targeting larger areas are needed to increase the efficiency and effectiveness of asbestos roof removal initiatives using multispectral satellite and aerial imagery.

The CNN method applied in our research is a classifier that has been highly effective in image recognition tasks, but it has not yet been widely used for identifying asbestos cement roofs (Krowczynska et al., 2020; Raczko et al., 2022). Efforts to identify asbestos-cement roofs are increasingly focused on enhancing the overall accuracy of classification (Torres Gil et al., 2023).

Similar accuracies to those achieved in this study have been published by Fiumi et al. (2012), Szabo et al. (2014) and Krowczynska et al. (2016). However, this research involved the use of hyperspectral images. Acquiring hyperspectral images is associated with high costs for both acquisition and subsequent processing. Therefore, finding more cost-effective alternatives without compromising accuracy is essential for broader and more practical applications in identifying asbestos-cement roofs. Exploring different imaging technologies and processing techniques could provide viable solutions for large-scale implementations.

Operational application, aimed at estimating the number of still-in-use asbestos-cement roofs, also requires an examination of the areas covered by previous studies, the methods employed, and the data obtained. It is essential to analyse the geographic scope, scales, and specifics of past research to develop effective strategies for identifying and assessing these roofs on a larger scale. This involves understanding which regions have been studied, the imaging and analytical techniques that were used, and the nature of the collected data to ensure that future efforts are both comprehensive and targeted, thereby optimizing resource allocation and improving the accuracy of the results.

The INSPIRE Directive (Infrastructure for Spatial Information in the European Community) aims to create a standardized spatial data infrastructure across the European Union to support environmental policies and activities that may impact the environment. This directive facilitates the sharing of spatial information among public sector organizations and improves public access to spatial data. One of the critical aspects of INSPIRE is the use of accessible and up-to-date orthophotos, which are essential for various applications, including urban planning, environmental monitoring, and the identification of hazardous materials like asbestos-cement roofs. By ensuring that high-quality, current orthophotos are available, INSPIRE enhances the accuracy and efficiency of spatial analyses and decision-making processes, contributing to better environmental management and public health outcomes.

Hyperspectral imaging, while providing highly detailed spectral information across numerous bands, is often prohibitively expensive for widespread use due to the high costs associated with data acquisition and processing. In contrast, orthophotos obtained under the INSPIRE Directive offer a more cost-effective alternative. These orthophotos, which are freely accessible and regularly updated, provide valuable spatial information that can be effectively used for various applications, including the identification of asbestos-cement roofs. Leveraging these freely available orthophotos can significantly reduce costs while maintaining sufficient accuracy for operational purposes, making them a practical choice for large-scale environmental monitoring and urban planning initiatives.

Additionally, the convolutional neural network (CNN) used in this study can be further trained for specific areas. Given its adaptability, it can be successfully applied to other research areas and beyond. By fine-tuning the network to accommodate local variations and specific characteristics of different regions, CNN's effectiveness in identifying asbestos-cement roofs can be significantly enhanced, making it a versatile tool for a wide range of spatial analysis tasks.

5. Conclusions

Warsaw, the capital city of Poland, presents a unique challenge for the identification of asbestos-cement roofs due to its diverse architectural landscape and extensive urban development. The city encompasses a mix of historical buildings and modern infrastructure, resulting in a heterogeneous roofing environment. This complexity makes Warsaw an ideal case study for testing and refining convolutional neural network (CNN) models for roof classification. High-resolution aerial imagery, combined with advanced image processing techniques, can facilitate the accurate mapping and quantification of asbestos-cement roofs within the city's densely populated districts. The findings from Warsaw can contribute to developing reliable methodologies applicable to other urban areas with similar characteristics.

The research findings highlight the necessity for continued studies aimed at developing a robust method for remote identification of asbestos-cement roofs, which could be applicable across other European Union countries. The current study has demonstrated promising results, yet further refinement and validation of the methodology are required to ensure its effectiveness and scalability in diverse geographic and architectural contexts. Establishing a universally applicable technique would facilitate large-scale asbestos monitoring and management, thereby contributing to improved public health and safety across the EU. Such advancements would also support regulatory compliance and aid in the efficient allocation of resources for asbestos abatement programs.

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