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URBAN GROWTH MONITORING- REMOTE SENSING METHODS FOR SUSTAINABLE DEVELOPMENT

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ABSTRACT:

Urban areas account for a small fraction of the Earth's surface but have a disproportionate impact on its surroundings regarding mass, energy, and resources. An exponential increase in the urban population has been observed since the mid-20th century. As expected by the United Nations (UN), by the year 2050, 68.4% of the world population will live in cities with a population of 20,000 or more. Due to enormous socio-economic pressures resulting from population expansion, urbanization and intensive changes in the landscape, an urban development program to make cities and human settlements inclusive, safe, resilient, and sustainable has become of the utmost importance since the 2005 World Summit in Rio and further adopted in 2015 by UN as the "2030 Agenda" for Sustainable Development. The study focused on monitoring the SDG 11 target 11.3.1. they are defined as a ratio of land consumption rate to the population growth rate because mapping urban land quickly and accurately is indispensable for watershed run-off prediction and other planning applications. There is no well-established, consistent way to measure either urban land sprawl or population growth. However, remote sensing methods and satellite-derived data make it possible to monitor urban growth rates over large areas in a relatively short time. There are many techniques for urban land cover automatically mapping. These techniques can be broadly grouped into two general types: those based on the input data classification, including pixel- and object-based classifications and those based on directly segmenting the indices, such as the commonly used normalized difference vegetation index (NDVI), normalized build-up area index (NDBI), and their modifications.

The authors used classical pixel (supervised classification with Spectral Angle Mapper classification and KNN methods) and object-based classification in the presented research. In addition, spectral indices, i.e., NDVI, NDBI and their modifications to derive build-up areas, were applied. Moreover, the authors focused on the recent deep learning and machine learning methods, i.e., the utilization of spatial-context information in multi-temporal data to learn hierarchical feature representations. All methods of detecting built-up areas were compared and assessed based on the available cartographic data.

1. INTRODUCTION

Urban areas account for a small fraction of the Earth's surface but have a disproportionate impact on its surroundings regarding mass, energy, and resources. An exponential increase in the urban population has been observed since the mid-20th century. As expected by the United Nations (UN), by the year 2050, 68.4% of the world population will live in cities with a population of 20,000 or more. Due to enormous socio-economic pressures resulting from population expansion, urbanization and intensive changes in the landscape, an urban development program to make cities and human settlements inclusive, safe, resilient, and sustainable has become of the utmost importance since the 2005 World Summit in Rio and further adopted in 2015 by UN as the "2030 Agenda" for Sustainable Development. The study focused on monitoring the SDG 11 target 11.3.1. they are defined as a ratio of land consumption rate to the population growth rate because mapping urban land quickly and accurately is indispensable for watershed run-off prediction and other planning applications. There is no well-established, consistent way to measure either urban land sprawl or population growth. However, remote sensing methods and satellite-derived data make it possible to monitor urban growth rates over large areas relatively quickly. Change detection based on remote sensing data is an essential method of detecting changes on the Earth's surface. It has a wide range of urban planning applications, i.e.; it can provide timely and synoptic views of urban land cover and environmental monitoring, agriculture investigation, disaster assessment, and map revision (Afify, 2011; Falco et al., 2013; Feranec et al., 2007; Hayes & Sader, 2001; Hegazy & Kaloop, 2015; İlsever & Ünsalan, 2012; Jenerowicz et al., 2019).

1.1 Change detection methods

To monitor the environment and make proper management, observing and analyzing changes in the infrastructure and environment are significant. One of the most efficient techniques for analyzing changes in urban areas is remote sensing. The usage of multi-time data from various sources is necessary for quantitative and qualitative change detection.

The change detection results will be influenced by many factors, e.g., the geometric relationship between the images used, the quality of the data, the type of infrastructure or the complexity of the environment, the techniques or algorithms used, the type of classification, as well as the skills and experience of the analyst (Lu et al., 2004). The first change detection methods were based on the pixel-based approach, i.e., on a comparison of pixel values. Over time, along with improving the resolution of images and increasing the images' details, feature-based methods have been developed (İlsever & Ünsalan, 2012). Therefore, change detection methods can be divided into digital processing, i.e., algebraic operations (image differencing (Karthik &

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Shivakumar, 2017), image rationing (Khanday & Kumar, 2016) image regression (Afify, 2011)), image transformations (spectral indices (Xie et al., 2014), i.e., NDVI (Gitelson et al., 1996); Principal Component Analysis (Abdi & Williams, 2010), classification (Wu et al., 2017)) and visual analysis, where the analyst's knowledge is the crucial element. However, visual analysis is time-consuming, especially when analyzing a large area or when imagery data is very detailed (Zhu & Woodcock, 2014).
There are many techniques for urban land cover automatically mapping. These techniques can be broadly grouped into two general types: those based on the input data classification, including pixel- and object-based classifications and those based on directly segmenting the indices, such as the commonly used normalized difference vegetation index (NDVI), normalized build-up area index (NDBI), and their modifications. Moreover, in recent years, integrated artificial intelligence (AI) techniques can be used to detect changes. AI techniques, also called machine intelligence or machine learning, can perform various data-processing tasks better. It can be defined as a system's ability to interpret external data correctly, learn from such data, and use those learnings to achieve specific goals and tasks through flexible adaptation.

2. DATA AND METHODS

In this study, open-source remote sensing satellite imagery data were used for monitoring the spatial distribution and growth of urban built-up areas in Poland, i.e., the analysis was conducted for selected counties in Poland- in total 21, that are characterized by different growth rates- Figure 1, Figure 2.

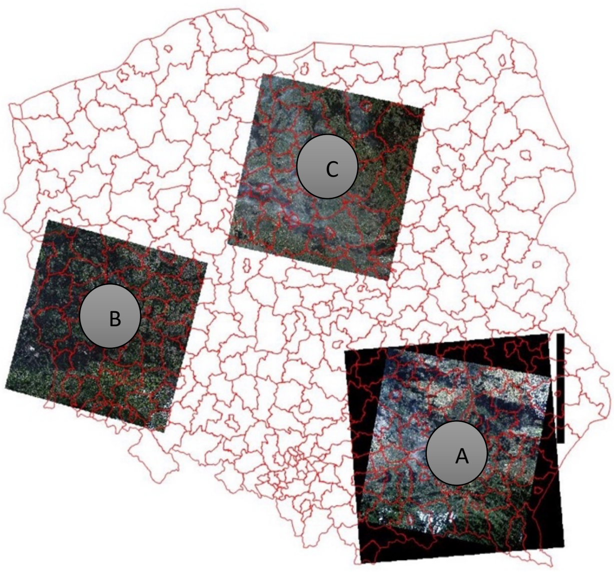

Figure 1. Areas of interest

For the study purpose, areas with different degrees of development in the north, west and south of Poland were used. They were mainly counties in the Lesser Poland, Lubuskie and Greater Poland provinces, as well as the Kuyavian-Pomeranian (C) provinces.

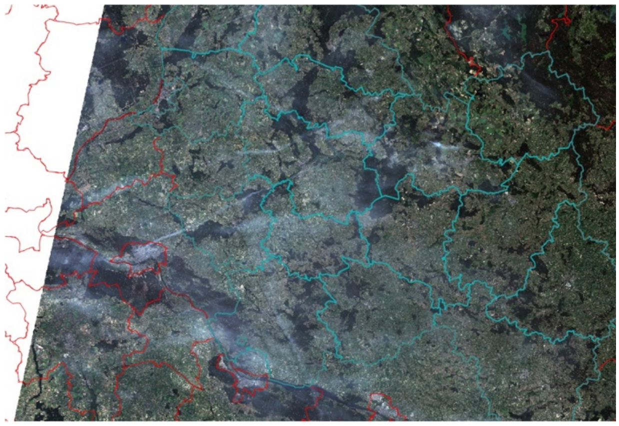

Figure 2. Examples of analyzed counties (marked as blue)

The authors focused on analyzing the development of urbanization in the years 2006-2012-2018 for only three zones in Poland that had the highest rate of urban growth in the past 20 years.
Satellite-derived imagery data were obtained from one of the longest-running satellite imagery acquisition programmes, i.e., NASA/ USGS Landsat. Landsat 5, Landsat 7 and Landsat 8, medium resolution multispectral data were used for the study purpose. The satellite images used in the study were acquired in a similar plants' phenological phase. Thus, images acquired between May and September were used. Cloud coverage did not exceed 10% for imagery.
All selected satellite data were adequately prepared by performing full radiometric correction (Quick Atmospheric Correction- QUAC) and geometric co-registration.
Definition of urban areas was adapted from Corine Land Cover guidelines (Caetano & Araújo, 2006; *CLC 2012*, n.d.; GIOŚ, n.d.; Hosciło & Tomaszewska, 2014), which are defined as artificial areas- such zones can be defined as areas mainly occupied by dwellings and buildings used by administrative/public utilities, including their related areas (associated lands, approach road network, parking lots). The Corine Land Cover database divides those zones into 13 types- Table 1.

1. Artificial Surfaces	1.1 Urban fabric	1.1.1 Continuous urban fabric
		1.1.2 Discontinuous urban fabric
	1.2 Industrial, comercial and transport units	1.2.1 Industrial or commercial units
		1.2.2 Road and rail networks and associated land
		1.2.3 Port areas
		1.2.4 Airports
	1.3 Mine, dump and construction sites	1.3.1 Mineral extraction sites
		1.3.2 Dump sites
		1.3.3 Construction sites
	1.4 Artificial, non-agricultural vegetated areas	1.4.1 Green urban areas
		1.4.2 Sport and leisure facilities

Table 1. Urban areas, according to CLC.

The authors used the classical pixel classification method (supervised classification with Spectral Angle Mapper classification and KNN methods) and object-based classification (OBIA) in the presented research. In addition, spectral indices, i.e., NDVI, NDBI, and BI and their modifications to derive build-up areas, were applied. Moreover, the authors focused on the recent deep learning and machine learning methods, i.e., the utilization of spatial-context information in multi-temporal data to learn hierarchical feature representations. All methods of detecting built-up areas were compared and assessed based on the available cartographic data.

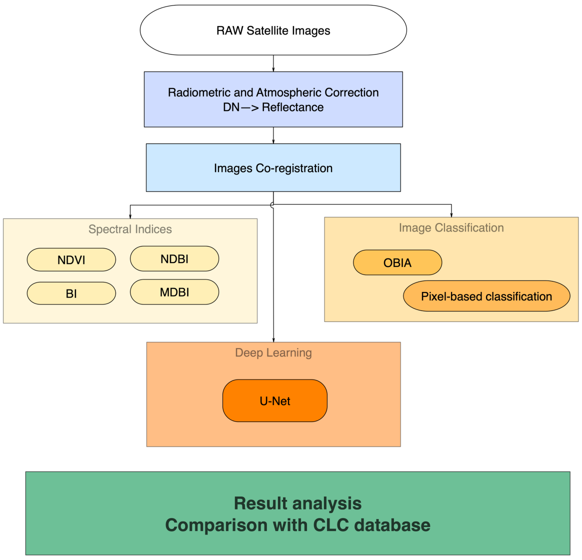

Figure 3. Data processing flowchart

2.1 U-Net for urban area detection

The U-Net method was chosen as the method of deep learning. U-Net architecture (Ronneberger et al., 2015), (Ulmas & Liiv, 2020), (Gerlach, 2015) has 23 convolutional layers, includes multi-channel 276 feature maps, and has a contracting path and an expansive path. There is the repetition of two 3X3 convolutions, after each of them a ReLU operation and 2x2 max pooling part.

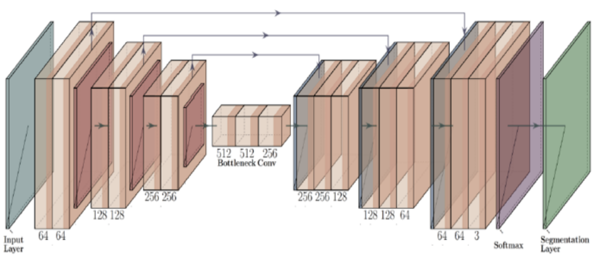

Figure 4. U-Net architecture

The architecture is yielded such a good performance on various biomedical segmentation experiments. It has a wide usage for many computer vision segmentation tasks due to working very few training data and still yields segmentation results precisely (Figure 4- the methodology for U-Net classification).

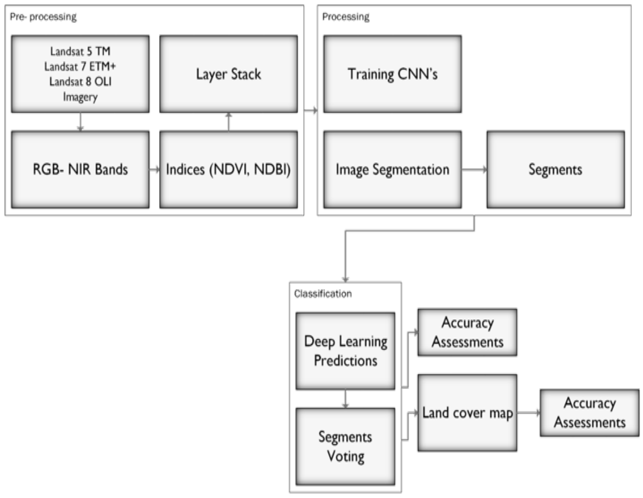

Figure 5. Urban area detection with CNN (U-Net)

U-NET has two branches: Convolution and max pooling operations are performed in the down-sampling branch, as with almost all CNNs. That branch—also called the contracting path—records the spectral and spatial context in the form of feature maps. The up-sampling path uses up-convolutions combined with the feature maps from the contracting path. Up-sampling functions replace pooling operators. That allows the localization information to be carried along from input to output and retains the contextual information.
In order to train the network, other satellite images for Poland were used that did not include the 21 counties of interest. Multispectral satellite images and training samples from the Landsat program were divided into 128 x 128 pixels patches. The network was trained using a TensorFlow based version of the U-NET algorithm coded in Python (Version 3.7 NVIDIA GEFORCE ®GT630 graphics card under Linux Ubuntu 18.04 based on 600 images.

3. RESULTS

The preliminary results of the analyses showed that the highest accuracy of the determination of built-up areas for the analyzed regions was obtained for the modified NDBI method and object classification and classification based on the KNN. Values of 95.2%, 96.4%, and 95.8% were obtained for these methods.

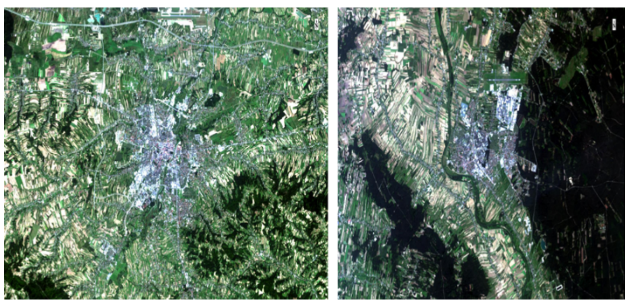

Figure 6. Example of original Image

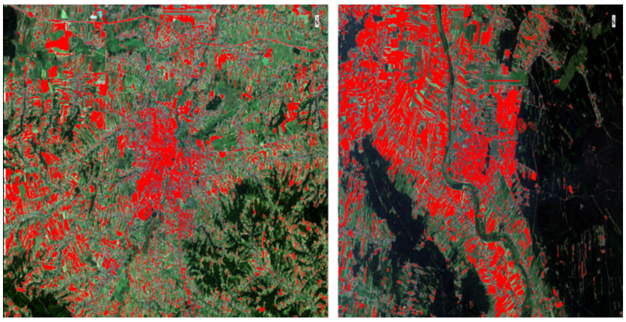

Figure 7. Example of NDVI result

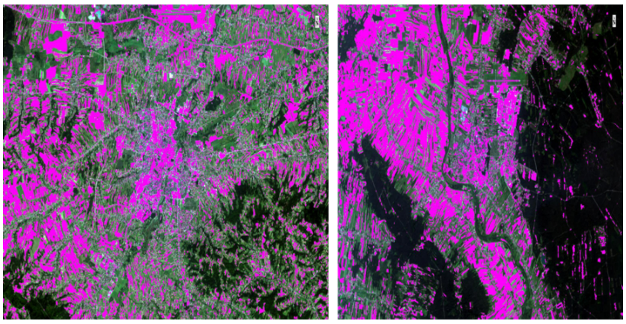

Figure 8. Example of NDBI result

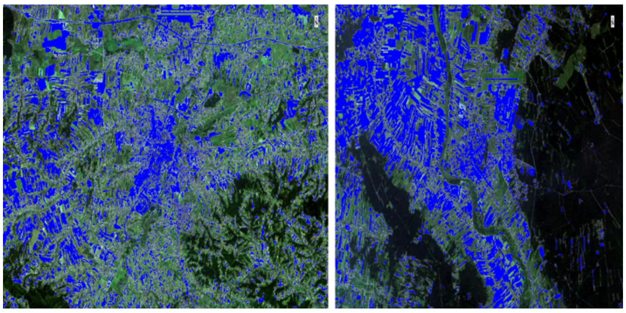

Figure 9. Example of BI (NDVI- NDBI) result

The classification based on the pixel value (SAM- Spectral Angle Classification (Girouard et al., 2004), maximum likelihood classification) and the object classification were also used.

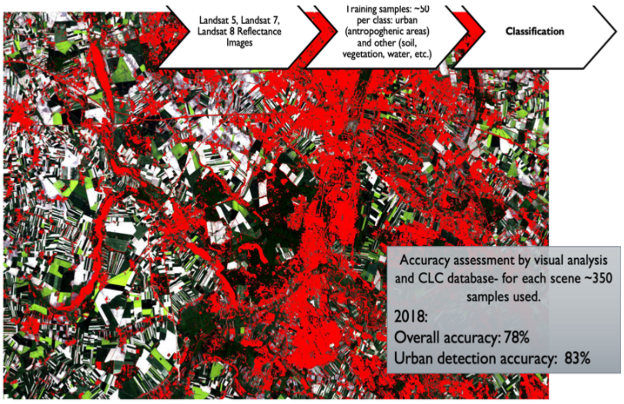

Figure 10. Maximum-likelihood classification example

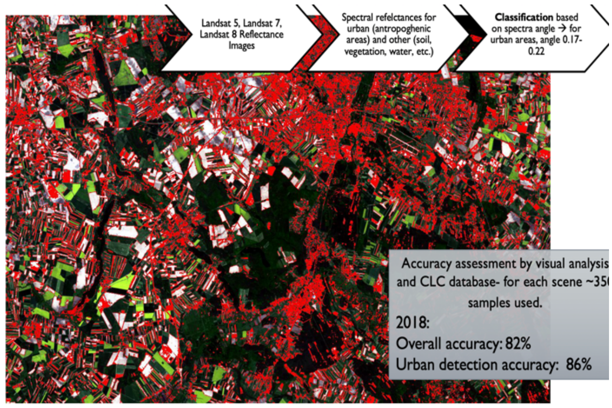

Figure 11. SAM classification example

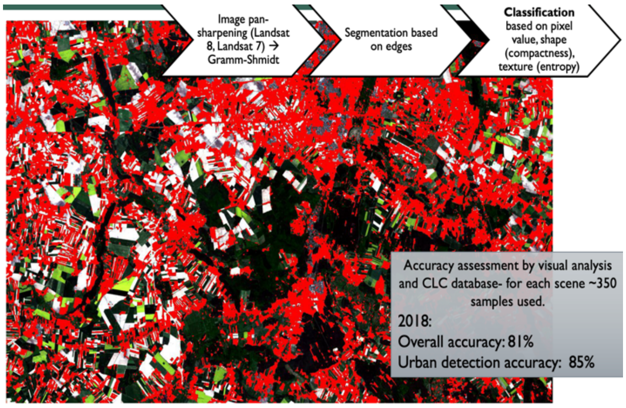

Figure 12. OBIA classification example

After the application of classical methods, AI techniques were applied, also called machine intelligence or machine learning, which can better perform various data-processing tasks after a thorough analysis of the subject of object detection using AI, it was decided to use one of the deep learning methods, artificial neural network based on U-NET.

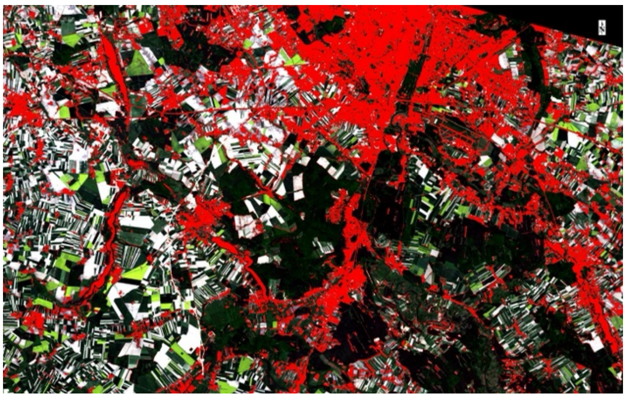

Figure 13. Example of Image classification with U-Net

Then, an assessment of the development of built-up areas was carried out. ML methods to detect land cover changes for the model made it possible to detect changes in built-up areas at the level of just over 78%. For the classification, the U-Net was used. However, the results are expected to improve after the database for the training model is completed. The results were then cross-checked with Corine Land Cover (CLC) data and with demographic data.

Standard accuracy assessment parameters for class metrics such as precision, recall, F1-Score, and Intersection over union (IoU) are computed for the predicted images using metrics of True Positive (TP), False Positive (FP), and False Negative (FN). Overall accuracy (OA) was an evaluation metric for the classification using U-Net- Table 2.

Land Cover	**Landsat 5**		**Landsat 7**		**Landsat 8**	
	FI%	**IoU%**	**FI%**	**IoU%**	**FI%**	**IoU%**
Urban	73.5	78.9	88.6	95.7	89.5	96.2
Other	87.6	91.2	93.8	98.1	91.2	97.8
Overall Accuracy	82.6		89.3		96.4	
Precision	91.1		95.9		98.6	
Recall	89.6		92.3		96.3	

Table 2. Accuracy results for U-Net urban area detection.

However, the results are expected to improve after the database for the training model is completed. The results were then cross-checked with Corine Land Cover (CLC) data and with demographic data.

That comparison provided a new way to understand the urban structure and its changes (Figure 11). Such insights are essential starting points for a new urban research program: creating globally and temporally consistent proxies to guide urban change. Classical methods for build-up areas detection, i.e. spectra indices pixel-based classification, give better results when bare soil is lacking. As presented in the research, the best results are for CNN (U-Net); the results are expected to improve after the database for the training model is completed.

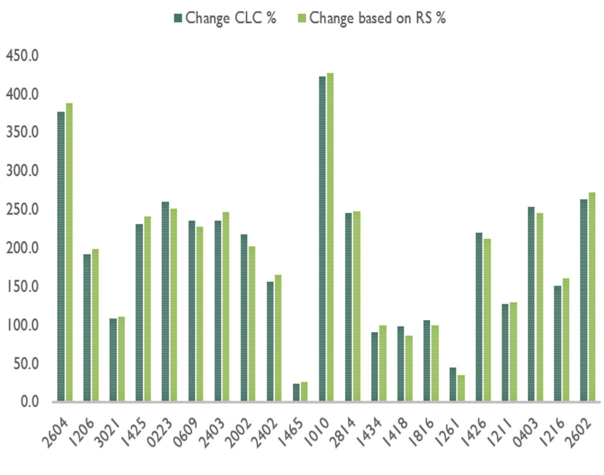

Figure 14. Results for DL classification

4. SUMMARY

The preliminary results of the analyses showed that the highest accuracy of the determination of built-up areas for the analyzed regions was obtained for the modified NDBI method and object classification and classification based on the KNN. Values of 95.2%, 96.4%, and 95.8% were obtained for these methods. Then, an assessment of the development of built-up areas was carried out. ML methods to detect land cover changes for the model made it possible to detect changes in built-up areas at the level of just over 78%. However, the results are expected to improve after the database for the training model is completed. The results were then cross-checked with Corine Land Cover (CLC) data and with demographic data. That comparison provided a new way to understand the urban structure and its changes. Such insights are essential starting points for a new urban research program: creating globally and temporally consistent proxies to guide urban change.
Classical methods for build-up areas detection, i.e., spectra indices and pixel-based classification, give better results when bare soil is lacking. The best results are for CNN (U-Net); the results are expected to improve after the database for the training model is completed.
That comparison provided a new way to understand the urban structure and its changes. Such insights are essential starting points for a new urban research program: creating globally and temporally consistent proxies to guide urban change.

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