Derivation of Urban Planning Indicators (UPIs) using Worldview-3 Imagery and GEOBIA Method for Split Settlement, Croatia

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Abstract: In most urban environments, loss of natural vegetation, the reduction of open spaces, and the rapid invasive transformation of the natural environment into impervious has happened. These changes can lead to a decline in life quality and in an increase of various economic, social, ecological, and infrastructural problems and risks. The complexity of the urban environment at various scales requires the application of high spatial and temporal resolution data in the process of urban planning. In this paper, specific urban planning indicators (UPIs), divided into two groups, have been derived for statistical circles (SC) of Split settlement in Croatia. Vegetation indicators (TCR - *tree cover ratio*, LCR - *lawn cover ratio*, GCR - *green cover ratio*) and indicators of urbanization (SCR - *street cover ratio*, BCR - *building cover ratio*, IMR - *impervious surface ratio*) were derived from the derived land cover model. It was generated from *WorldView-3* (WV3) imagery with the GEOBIA method. A supervised machine learning technique *support vector machine* (SVM) was used. A significant spatial variability between UPIs at SCs was observed. The UPIs values at the studied level are the reflection of the historical spatial-functional development of the Split settlement. These type of UPIs can be used at the neighborhood level of urban planning and analysis of different issues in an urban environment.

1 INTRODUCTION

Urbanization is one of the most striking features of our history, especially since the industrial era. It is characterized by constant, rapid growth. Based on the UN-projections by the year 2050, more than 80% of the world population will live in urban areas. In European countries, the level of urbanization is around 74% (Duffin, 2019).

Urbanization has led to the replacement of natural vegetation-dominated surfaces by various impervious materials. This had a significant impact on the environment. Some of the observed consequences are reduction of the open spaces (Liu, 2009), increased risk of pluvial floods (Du et al., 2015), endangerment of the drinking water quality (Wang et al, 2020), the appearance of the urban heat islands (UHI) (Petralli et al., 2014), various environmental pollution problems (Sleavin et al., 2000) and ultimately a decline in life quality (Sinha, 2019). Therefore, efficient urban planning has become a *central tool of governance, through which these major issues of urban development will have to be addressed* (Watson, 2009, pp.3). This challenge requires new analytic approaches and new sources of data and information (Miller and Small, 2003) in urban planning.

There are numerous definitions of urban planning (Hall, 2002; Davidson 1996; Anguluri, and Narayanan, 2017). It is regarded as a complex, technical, and political process that includes land use control, urban environment design, and environmental protection. Its primary purpose is to improve the decision-making process (Levy, 2016). In the context of urban planning, there is a notion of the urban environment (Sénécal, 2007, Blaschke et al. 2011) which is defined as a physical place that includes different land use patterns, built infrastructure, and transportation system (Brownson et al., 2009; Gong et al., 2016). The increasing availability of geospatial data in combination with traditional data sources could facilitate the development of new tools in understanding urban

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environment complexity (Blaschke et al. 2011). Urban environment planning requires a multidisciplinary approach and the application of modern research methods (Abbate et al. 2003, Blaschke et al., 2011, Tenedório et al., 2016) through the application of various geospatial technologies (GST) (Herold et al., 2003, Lo, 2007; Bodzin, 2009, Blaschke et al. 2011). GST is defined as a set of methods, techniques, and procedures used in modeling of complex processes and features in different levels of detail (LoD) depending on the research purpose (Marić, et al., 2019). GST includes GIS, elements of remote sensing (RS), a global positioning system (GPS), and other related geospatial technologies (Dibiase et al., 2006, LeGates et al., 2009). The application of various GST enables the derivation of various urban planning indicators (UPIs) (Zhao et al., 2011, Rosales, 2011, Petralli et al., 2014, Chrysoulakis et al., 2014, Chatzipoulka et al., 2016) which serves decision-makers, with measuring performance role, in the planning of urban environment (Zhao et al., 2011). The UPIs are usually determined at the very beginning of planning and serve as a basis for the entire planning and process design. UPIs are crucial in the monitoring of urban morphology and urban development intensity. They are derived for different purposes, among which stands out research about urban thermal islands (Zhao et al., 2011, Lin et al., 2017), the building of sustainable cities, and sustainable urban development (Rosales, 2011, Shen et al., 2011, La Rosa, 2014, Chrysoulakis et al., 2014), and achieving sustainable urban governance (Chrysoulakis et al., 2014). The LoD and spatial resolution of data used to derived specific UPIs depends on the level (eg. local, neighborhoods, metropolitan, regions) (Bryant, 2006) or scale (macro - micro) (Elshater, 2017) at which the urban planning process is performed. In this research, we use high-resolution *WorldView-3* imagery to derive specific UPIs for the city of Split, Croatia. The research was performed within the *INTERREG Italy-Croatia PEPSEA (Protecting the Enclosed Parts of the Sea in Adriatic from pollution)* project. UPIs were calculated from a land cover model which was derived using geographic object-based image analysis (GEOBIA) (Hay and Castilla, 2008).

2 STUDY AREA

Split is the administrative center of Split-Dalmatia County. It is the largest city in the Dalmatia region and the second-largest city in the Republic of Croatia (HR) (Fig. 1B). At the latest census (2011), the total population of Split was 178 102. Split is located on the peninsula and surrounded by hills. Mosor hill is located on the northeast side of the city (Fig. 1C). Kozjak hill is located on the northwest side. Split is surrounded by the islands of Brač, Hvar, Šolta, and Čiovo (Fig. 1B). The city of Split consists of 92 statistical circles (SC) (Fig. 1C). A statistical circle is one of the smallest statistical spatial units in the HR. They were established in 1959 and revised in each previous census. They represent a permanent network of spatial units, covering the entire mainland of the HR (Šiljeg et al., 2018).

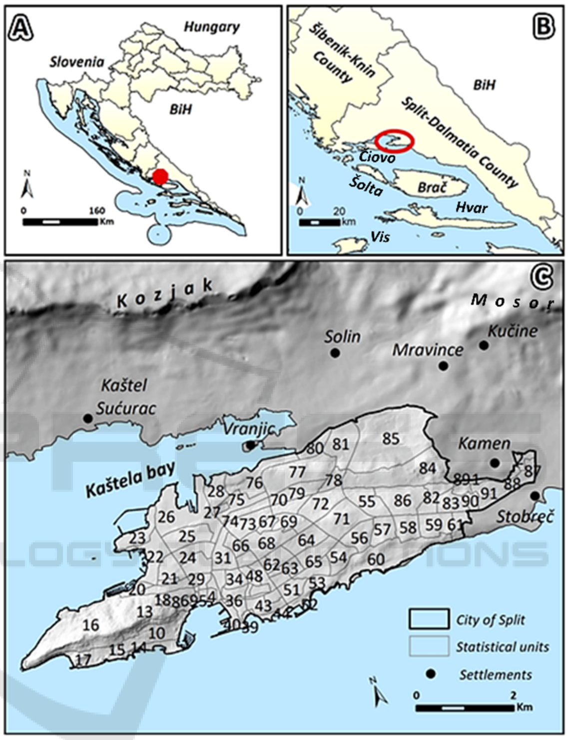

Figure 1: A) Split settlement in the HR; B) location of Split peninsula in Split-Dalmatia Country and B) statistical circles (IDs of Split settlement.

ID (Figure 1) - Name of statistical circle
1-SK0049298, **2**-SK0049301, **3**-SK0049310, **4**-SK0109819, **5**-SK0109827, **6**-SK0109835, **7**-SK0109843, **8**-SK0109851, **9**-SK0109860, **10**-SK0109878, **11**-SK0109886, **12**-SK0109894, **13**-SK0109908, **14**-SK0109916, **15**-SK0109924, **16**-SK0109932, **17**-SK0109959, **18**-SK0109967, **19**-SK0109975, **20**-SK0109983, **21**-SK0109991, **22**-SK0110019, **23**-SK0110027, **24**-SK0110035, **25**-SK0110043, **26**-SK0110051, **27**-SK0110060, **28**-SK0110078, **29**-SK0110086, **30**-SK0110094, **31**-SK0110108, **32**-SK0110116, **33**-SK0110124, **34**-SK0110132, **35**-SK0110159, **36**-SK0110167, **37**-SK0110175, **38**-SK0110183, **39**-SK0110191, **40**-SK0110205, **41**-SK0110213, **42**-SK0110221, **43**-SK0110230, **44**-SK0110248, **45**-SK0110256, **46**-SK0110264, **47**-SK0110272, **48**-SK0110299, **49**-SK0110302, **50**-SK0110329, **51**-SK0110337, **52**-SK0110345, **53**-SK0110353, **54**-SK0110361, **55**-SK0110370, **56**-SK0110388, **57**-SK0110396, **58**-SK0110400, **59**-SK0110418, **60**-SK0110426, **61**-SK0110434, **62**-SK0110442, **63**-SK0110469, **64**-SK0110477, **65**-SK0110485, **66**-SK0110493, **67**-SK0110507, **68**-SK0110515, **69**-SK0110523, **70**-SK0110531, **71**-SK0110540, **72**-SK0110558, **73**-SK0110566, **74**-SK0110574, **75**-SK0110582, **76**-SK0110604, **77**-SK0110612, **78**-SK0110639, **79**-SK0110647, **80**-SK0110655, **81**-SK0110663, **82**-SK0110671, **83**-SK0110680, **84**-SK0110698, **85**-SK0110701, **86**-SK0110710, **87**-SK0113034, **88**-SK0113069, **89**-SK0113107, **90**-SK0113115, **91**-SK0113123, **92**-SK0148652

3 MATERIAL AND METHODS

3.1 GEOBIA Extraction of Land Use Model using Worldview-3 (WV-3) Imagery

The land cover model of the Split settlement was derived from WorldView-3 (WV-3) satellite imagery. WV-3 was launched on 13 August 2014 by *Digital Globe* (Ye et al., 2017). WV-3 is one of the most advanced commercial satellites. It provides one of the highest spatial resolutions for multispectral data (0.31 m for panchromatic data and up to 1.24 m for multispectral bands) (Maxar Technologies, 2019). The derivation of land cover was done through several steps (Fig. 2).

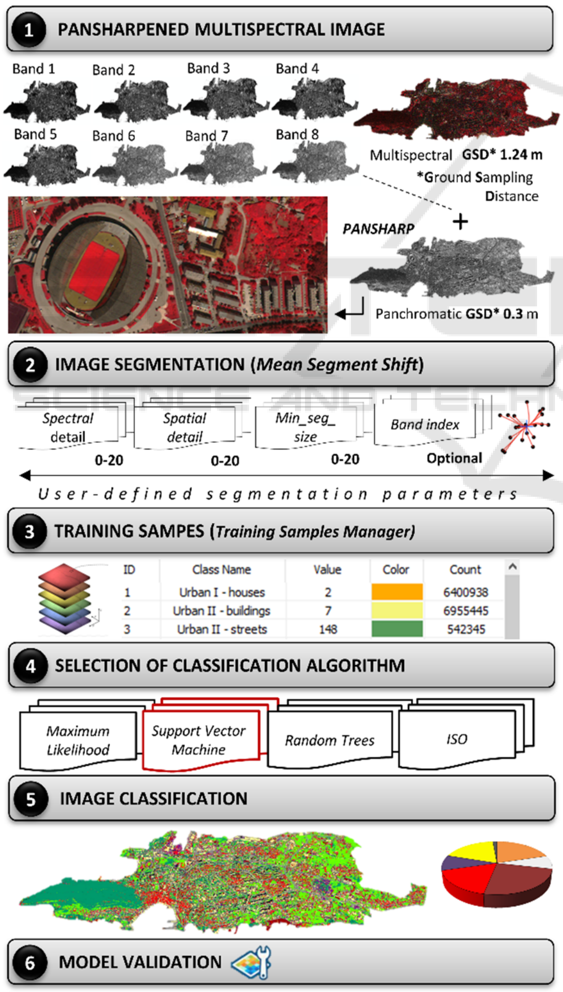

Figure 2: Scheme of WV-3 image processing using GEOBIA method.

The first step involved creation of a multispectral image (MS) using the *Composite bands* tool. Then spatial resolution of the MS was enhanced using a panchromatic image (Choi et al., 2019). This was done in the *Geomatica Banff 2018 Trial* with PANSHARP tool. The product of this process was pansharpened MS.

Then segmentation of pansharpened image was done. The *Segment Mean Shift* tool in ArcGIS software was used. Quality of land cover is highly determined by the selection of user-defined parameters: *Spectral Detail, Spatial Detail, Min_Segment_Size,* and *Band Indexes*.

The *Spectral Detail* sets the level of importance given to the spectral differences of features in the imagery (ESRI, 2020).

The *Spatial Detail* sets the level of importance given to the proximity between features. In both cases, values range from 1 to 20.

The *Min_Segment_Size* parameter identifies blocks of pixels that are too small (in relation to defined value) to be considered as a fragment (ESRI, 2020). All segments that are smaller than the specified value will be merged with their best fitting neighbor segment.

Band_Indexes parameters refer to the selection of the bands used in multispectral image segmentation. It is necessary to choose bands that offer the most noticeable differences between features. However, there is no clearly defined rule about the optimal segmentation parameters values (Benarchid and Raissouni, 2014).

To define the best combination for UPIs extraction, we have tested different parameter values using (Fig. 3) the visual interpretation method (*trial-and-error*) (Benarchid and Raissouni, 2014).

Three segmented images were generated using different parameter values (Fig. 3). The visual interpretation showed that the third segmented model gave the best result (Fig. 3). In it, the values of *spectral* and *spatial detail* are high enough to separate features of similar spectral characteristics and to create not too spatialy smooth classes. On this model training samples are taken for identification of the land cover classes. About fifty training samples were marked for each defined class (n=8).

In the next step, train Esri classifier definition (.ecd) file using the *Support Vector Machine* (SVM) was created. Some researches have shown that SVM in urban environments (Kranjčić et al., 2019) is achieving higher classification accuracy than traditional methods (Chen et al., 2019). In the final step, the land cover model for Split settlement was generated (Fig. 2). In future research, the accuracy

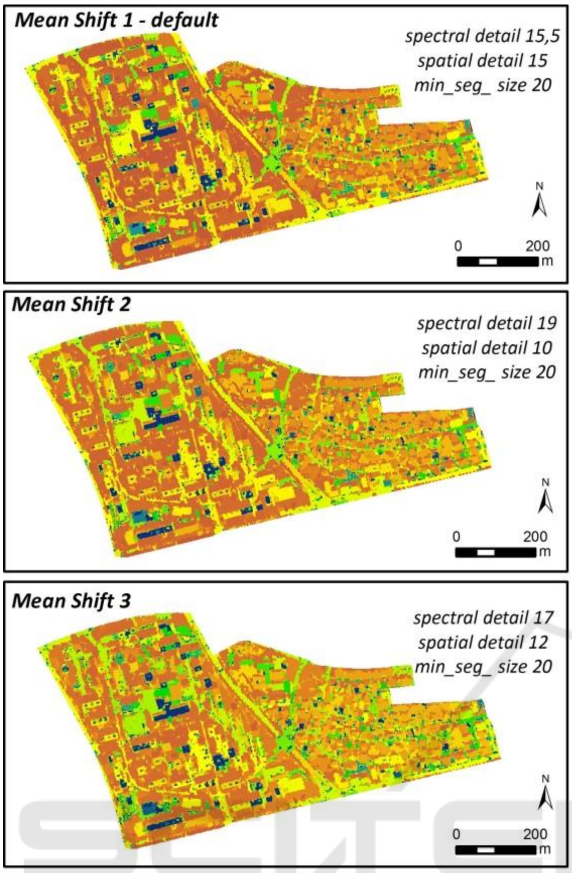

Figure 3: Tested segmentation parameter values.

assessment of land cover (overall accuracy and class by class) will be performed using the very high-resolution multispectral model generated with *Mica Sense RedEdge-MX* mounted on *Matrix 600 Pro*.

3.2 Derivation of Urban Planning Indicators (UPIs)

The UPIs for each statistical circle were derived from the generated land cover. UPIs used in this study were:

1. *Lawn Cover Ratio* (LCR): percentage of the study area that is covered by low vegetation (%);
2. *Tree Cover Ratio* (TCR): percentage of the study area that is covered by trees (%);
3. *Green Cover Ratio* (GCR): percentage of the study area that is covered by any kind of vegetation (%) (GCR = LCR + TCR);
4. *Street Cover Ratio* (SCR): percentage of the study area that is covered by concrete surfaces (%);
5. *Building Cover Ratio* (BCR): percentage of the study area that is covered by buildings (%)
6. *Impervious Surfaces Ratio* (ISR): percentage of the study area that is covered by impervious surfaces (buildings + concrete surfaces, houses) (%).

The first three UPIs are recognized as vegetation indicators of urban planning. They are important because the spatio-temporal distribution of vegetation is regarded as a fundamental variable in some aspects of urban planning. The use of such vegetation indicators is a common approach in vegetation monitoring. The other three UPIs (SCR, BCR, and ISR) are indicators of urbanization and major contributors to the environmental impact of urbanization.

4 RESULTS AND DISCUSSION

4.1 Land Cover Model

Total eight land use classes have been identified and extracted; tree cover, lawn cover, street cover, buildings, houses, macadam[4], shadows, and other objects (Fig. 4). Shadows are observed as a deficiency in this MS imagery. This has become especially notable in the urban environment modeling where they are potentially the main source of misclassification (Zhan et al, 2005). This problem is particularly pronounced when using advanced sensors with very high resolution (Shahi et al., 2014). Therefore, in this research shadows are detected and classified as a separate category (Zhang et al., 2018).

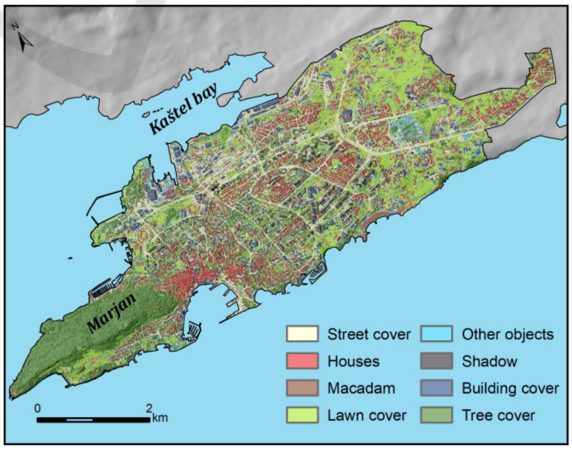

Figure 4: Land cover model of Split settlement.

[4] Macadam is broken stone of even size used for surfacing roads.

In this case study, most of them are detected on the northern side of the objects due to sun position during the satellite recording and are caused by a pronounced height of specific objects. The percentage of shadow class in the total area of SK varies significantly The highest percentages (around 15%) are found in smaller statistical circles (SK0110485, SK0110361) in which tall, residential buildings predominate.

4.2 Urban Planning Indicators (UPIs)

The main results of this study are derived UPIs (Fig. 5). Vegetation indicators have a higher percentage in the outskirts of the city, with the exception of the SK0109932 located in the western part of the city, dominated by the Marjan Forest Park which has the highest GCR among all circles (92.38%). Forest-Park is one of eleven nature protection categories in Croatia. Tree cover is making 85.72% of the SK0109932. The high GCR is also noticed in adjacent units south (SK0109959, SK0109908) of Marjan and in the eastern part (SK0110701) where GCR mostly consists of lawn cover (Fig. 5). This SK includes the Mejaši, a relatively young neighborhood that was merged with the city in the 2000s. In recent times new residential buildings have been constructed in this area. As expected, these statistical circles have the lowest ratio of impervious surfaces.

The old city center along with the wider city center area stands out as the most built-up part,. These units (SK0109827, SK0109860, SK0109843, SK0110205, SK0109894, etc.) are characterized by a prevalence of impervious surfaces (67-82%) and the lack of green areas. The most dominant type of impervious surfaces in this area are streets and buildings. These are older residential neighborhoods (Klempić, 2004). The northern outskirts (SK 0110582, SK 0110655) of the city are also characterized by a high presence of impervious surfaces (Figure 5). However, this part of the city is highly industrialized. Statistical circles characterized with the highest values of SCR (SK 0110205, SK 0110582, SK 0110060, SK 0110574, SK 0110655, SK 0110647) are located nearby industrial zone, central bus station, and passenger port.

A large percentage of the IMP (buildings, roads, houses) in statistical circles is not surprising given the history of spatial-functional development of the Split settlement. Namely, in the period from the Second World War to the 1990s, housing construction in Split was marked by socially-oriented collective construction with the objective to build as many residential buildings as possible on the smallest area possible. After the intensified industrialization process on the outskirts of the city, due to cheaper land, the construction of individual, mostly illegal housing units is taking place, which in the 1990s became the dominant form of housing construction (Klempić, 2004).

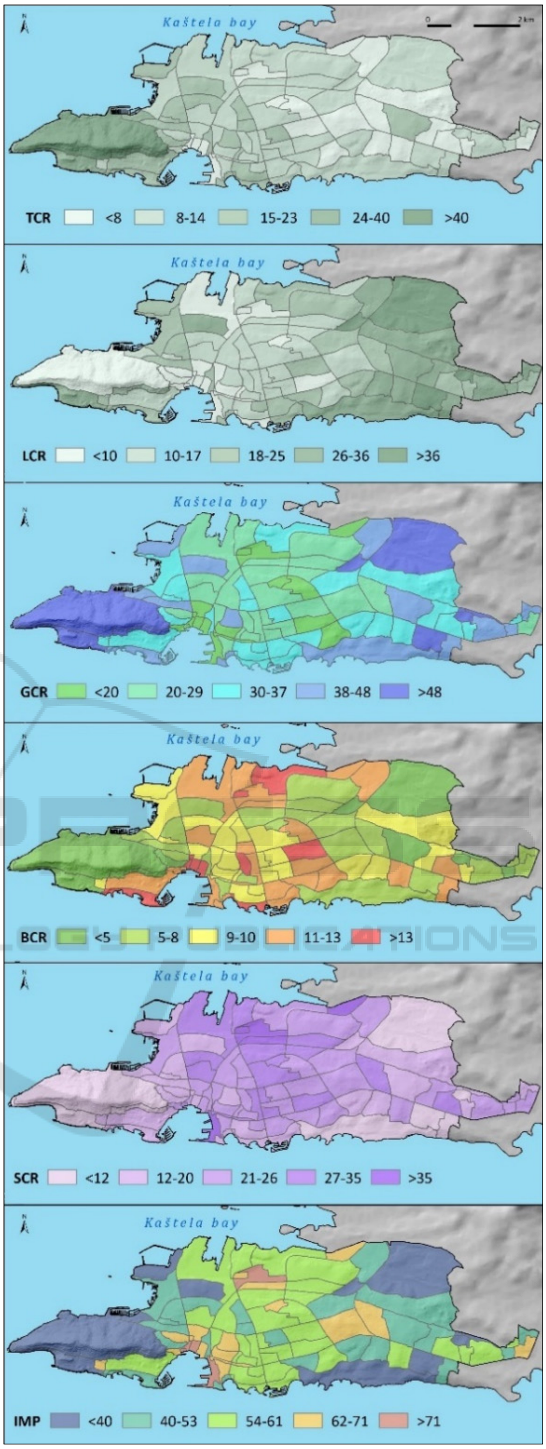

Figure 5: Derived UPIs for Split settlement.

To our knowledge, there are not many papers in which WV3 imagery was used to generate specific UPIs. In this study, it was demonstrated that WV3 imagery provides a good background to generate spatially detailed and up-to-date land cover data for a large urban area. This data is invaluable input for many activities within urban planning and development.

5 CONCLUSION

In this paper, we have demonstrated the use of WV-3 imagery and the GEOBIA method in the derivation of UPIs for the Split settlement. These types of UPIs can be used at the neighborhood level of urban planning and analysis of different issues in an urban environment. UPIs provided in this study, can form a basis for future planning and spatial organization of Split settlement. Significant spatial variability between UPIs is observed at the level of the statistical circles. The UPIs values at the studied level are the reflection of the historical spatial-functional development of the Split settlement. Urban expansion of the Split city is limited by its geographical location and orographic features of the surrounding area. Therefore, further development of the city is envisaged within the existing boundaries. In that context, the importance of knowing the exact, up-to-date UPIs cannot be overemphasized.

In future research, we are planning to analyze the UPIs within the specific SK using MS images of very-high resolution (<5 cm). Such detailed data would enable the accurate assessment of the UPIs generated from WV3 imagery. Also, it could help in establishing a system of indicators for urban management and in providing the assistance in monitoring of urban development at micro-level of research.

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