BORDER POROSIRY AND LANDSCAPE CHARACTERISTICS: A GIS-BASED APPROACH FOR SEGMENTING THE BORDER IN CARINTHIA, AUSTRIA

by
Nao Hisakawa
San Diego State University

Research conducted at Carinthia University of Applied Sciences, Villach, Austria

Summer 2011

ABSTRACT

National borders play an important role in everyday life. Interest in border studies has increased with recent changes in geographical locations of the border or the fluctuation of the permeability of the border between some countries, such as in the European Union. Whether the nations are trying to increase traffic flow of the border or to implement stricter border control, having appropriate information of the border is crucial for effective policymaking.

The objective of this research was to identify areas of high porosity, or high permeability, for pedestrians within the southern national border region in Carinthia, Austria using geographic information and geocomputational methods. Two unsupervised classification methods, the fuzzy K-means clustering and the Self-organizing map, were used to segment the border into homogeneous zones according to topographic and infrastructural attributes. The fuzzy K-means clustering method was chosen for its ability to allow for a continuous approach to classification. With this method, an object can have membership to multiple classes which is a more realistic reflection of the natural world than discrete clustering, where each object can only belong to one class. However, the fuzzy K-means clustering method does have disadvantages, i.e. the user must determine the number of classes and the input parameters are required to be in continuous format. The second classification method, the Self-organizing map, is a type of artificial neural network and was chosen for its ability to automatically determine the number of classes and handle categorical data. The Self-organizing map is unique because it can process high dimensional data into low dimensional display while preserving the topology and spatial distribution of input parameters. The results of the two classification method suggest that the fuzzy K-means classification is more effective than the Self-organizing map for this situation. However, more research needs to be done to determine which scenarios these algorithms can be used optimally.

The information obtained from this research provides an insight into the permeability of the border region between Carinthia, Slovenia, and Italy to pedestrian traffic and is useful for decision making process of tourism development and road transportation management. Further, the method developed to identify high porosity areas within the southern national border area of Carinthia, Austria, can be applied to other national borders to identify zones for different purposes in fields such as demography, finance, and climate.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ACKNOWLEDGEMENTS

This research was funded by the Marshall Plan Foundation. I would like to thank Dr. Gernot Paulus of Carinthia University of Applied Sciences for guiding this research and providing data. I would also like to thank Dr. Piotr Jankowski of San Diego State University for providing this research opportunity as well as his support throughout the project. Finally, data provision by the Carinthian Geographic Information System KAGIS and the Forest Technical Survey for Torrent & Avalanche Control in Carinthia is gratefully acknowledged.

CHAPTER 1

INTRODUCTION

Borders play a large role in people's daily lives as they shape cultural and ethnic identities of an individual. Although borders are generally invisible, they impact society by determining the extent of inclusion or exclusion from groups as well as differences between these groups (Newman, 2006a). Managing borders is important because it determines the difficulty level of border crossings of people as well as goods and ideas (Newman, 2006a). As the study of border spreads, so do disciplines that conduct border studies. While the meaning of the border is different for geographers, sociologists, historians, and politicians, contemporary border studies highlight the interconnectedness of these disciplines, and of physical geography (Newman, 2006b). The more relaxed borders would seemingly cause a decreased interest in border studies, but there has been a rise in the number of border-related conferences and workshops since 1995, which is an indication of an increased interest in this field (Newman, 2006a). With this, there has been a renewed interest in geography's involvement in international relations (Star, 2000). Studying borders remain important because people are aware that they are complex and intimately related to our physical and human environment (Brunet-Jailly, 2005).

One of the popular border study regions involves the European Union (EU). Although the actual borders do not change with nations joining the EU, the dynamics of the border between intra-EU and inter-EU are greatly affected. The general purpose of the formation of the EU was to overcome conflicts and preserve peace between the nations (Diez, Stetter, and Albert, 2006). The EU implemented the Single Market Policy, which supports the free movement of people, goods, services, and capital by bringing down the barriers to give European citizens easier access to EU's 27 countries (European Commission, 2010a). This gives European citizens the freedom to study, work, and retire in another EU nation as well as travel without visas (European Commission, 2010b). To encourage EU citizens to move around within the EU, European Commission has begun a cross-border cooperation program, also known as territorial cohesion, to address problems regarding border crossing by cross-border agreed analyses and re strategies. The objectives for this program include but are not limited to encouraging entrepreneurship in the development of tourism, culture, and cross-border trade, improving joint management of natural resources, developing joint use of infrastructure, and increasing employment opportunities (European Union Regional Policy, 2007). This program would decrease regional disconnection and allow Member States to learn from each other more easily, hence contributing to the EU to work optimally European Union Regional Policy, 2007). However, the opening of borders within the EU does not immediately cause the religious, cultural, economic, social, or ethnic hybridization (Newman, 2006b). Although regional diversity is valued, the interconnectedness of intra-EU countries is sought after in order for the EU to economically prosper. In order to successfully achieve this goal, the borders need to be analyzed from many different perspectives. Among social, political, and cultural perspectives, information obtained from physical geography analysis is important to assist in the policy making process of the EU.

There are many different types of land within the 27 countries of the EU. Mountainous areas are one of the land types that exist in many countries in the EU, and cover approximately 39% of land in the EU (European Commission, 2001). Mountainous areas are an important part of the European Union but are generally seen as geographical barriers because they are difficult to traverse. Although activities mostly center in the valleys and other usable land, increased traffic of goods have cause these areas to become transport bottlenecks which leads to concerns over safety risks and the environment (European Commission, 2001). Further, most mountainous regions have problems becoming economically viable as 95% of these areas receive funds for development or socioeconomic conversion (European Commission, 2001). This is a strong indication that these regions are rarely able to become economically self-sustaining.

Austria's state of Carinthia includes mountainous regions as well as shares its border with two other EU countries, Slovenia and Italy. These factors make it an interesting candidate for border analysis study. Carinthia's southern border that neighbors Slovenia and Italy is important for cross-border cooperation and the mountainous regions near the southern border are of special interest to the European Union where mountain regions represent a priority (European Commission, 2001). In addition, there are local efforts within Carinthia to reestablish ancient roads that were used by people to transport goods, called the Julia Augusta (http://www.turismoruralefvg.it/page.php?l=2&path=5_30). The Julia Augusta project provides cultural and touristic routes as well as information on these roads.

This paper reports the results of a study in which the southern border of Austria's state of Carinthia was analyzed according to its physical geographic landscape as well as infrastructure and assigned a porosity value. The term porosity refers here to the level of ease for pedestrians to cross any given border zone. The easier it is for people to cross, the higher the porosity value.

The motivation for this study is to deepen the understanding of the geographical environment between Carinthia and Slovenia and Italy. Since the physical geography of the border is interrelated with other aspects of the border such as social and political, the results of this research can influence policies aimed at the development of the region shared by three countries. Information obtained from this study may be valuable to organizations such as the Association of European Border Regions, whose aims include identifying problems, representing common interests, coordinating inter-region cooperation and encouraging information exchange (Association of European Border Regions, 2010). More specifically, information obtained from this study can assist with decision making processes in tourism and transportation problems. The increased ease of traveling between the EU nations is beneficial to the economy of the countries involved. The European Commission has identified tourism as a significant contributor to employment and to social benefits for local communities as well as providing a framework for unique cultures and environments (European Commission, 2003). The border segmentation method can also be used with other input parameters such as those related to population, climate, or financial costs, and can be applied to other levels of scale, such as counties and cities, for studies with many different purposes.

CHAPTER 2

RESEARCH OBJECTIVES

There were two overall goals of this project:

1. to develop a method to analyze the physical landscape characteristics of Carinthia's southern border that is shared with Slovenia and Italy and
2. to identify areas of high porosity, i.e. areas that are easy for pedestrians to cross within this border region.

CHAPTER 3

LITERATURE REVIEW

GIS IN BORDER STUDIES

Modern GIS techniques enable us to perform detailed spatial analysis. Spatial analysis can take real-world processes and manipulate the data in order to identify data trends, create new relationships from the data and visualize complex relationships between datasets thus making new information available (Jovanović and Njeguš, 2008; McAdam, 1999). GIS-assisted analysis can result in better decision making (Jovanović and Njeguš, 2008; McAdam, 1999). Hence, it is a powerful tool in analyzing border areas in which projects potentially involve large datasets, multiple datasets, and require effective visualization of the information. Integrating GIS in border studies allows researchers to address specific spatial questions about the border rather than simply observing the physical border lines (Star, 2000).

Geographic Information Systems (GIS) and spatial analysis techniques have been applied in the field of border studies. Within The European Union, a program called the European Observation Network for Territorial Development and Cohesion (ESPON) has been dedicated to understanding spatial development and dynamics in the EU (http://www.espon.eu/main/), The ongoing research projects under ESPON produce new knowledge of spatial trends, impact of EU policies and development opportunities which were made available to policymakers, stakeholders, and other parties with interest in the development of EU (European Union Regional Policy, 2007). Integrating spatial analysis in EU studies has continued to provide valuable information for transnational and cross-border cooperation activities, and has encouraged the inclusion of European perspectives in the development for regions, cities, and larger territories (European Union Regional Policy, 2007).

Another project commissioned by the European Union is the Iron Curtain Project. Before 1990, the countries along the iron curtain had very little cooperation and coordinated policies. This project was implemented to avoid potential conflict especially with ongoing integration efforts for these countries to be part of the EU. The objective of this project was to develop and implement policies for sustainable development at the cross border regions along the iron curtain, which included Norway/Russia, Germany West/East, Germany/Czech Republic, Austria/Czech Republic, Austria/Hungary and Greece/Bulgaria (Iron Curtain Consortium, 2005). For example, one component within the Iron Curtain Project was to determine the connection between agricultural land use and the main objectives of the natural land (Iron Curtain Consortium, 2004). This project demonstrated the usefulness of GIS in borer studies.

GIS has also been used to study migration patterns between borders in terms of border permeability (Coulter et al., 2010), or walking pattern of an adult (Stephenne and Zeug, 2007). Border permeability can have different meanings depending on the context in which it is being studied; i.e. transportation and illegal immigration patterns. In the context of transportation, permeability refers to the level of difficulty for vehicles to cross the border zone. This information can be used to manage traffic flow by improving existing roads that have low permeability and developing new routes in suitable areas. In the context of illegal immigration, permeability refers to the level of difficulty for any vehicle carrying illegal immigrants to cross or illegal immigrants on foot to cross the border zone. Knowledge of such areas can influence border patrol strategies and improve monitoring efficiency.

VARIABLES INFLUENCING PEDESTRIAN MOBILITY

Land cover and terrain features influence the rate of pedestrian travel and the amount of time that is needed to travel a given distance (Kaiser and Stow, 2007). Vegetation type can slow down a pedestrian by acting as a barrier of the route of travel, or can aid the pedestrian by increased traction due to soil stabilization (Kaiser and Stow, 2007). Our daily experience shows that walking over a grassy area takes less energy and time than walking over a surface with thick vegetation cover (Kaiser and Stow, 2007). The slope and aspect of the terrain determines the magnitude and direction of hills. It is intuitive that the degree of uphill and downhill terrain will affect the rate of walking, with uphill causing slower walking rates and downhill causing faster walking rates, with maximum speed occurring on a gentle downhill slope (Kaiser and Stow, 2007). Finally, roads and trails reduce the level of walking difficulty by creating pathways through vegetation and hills. Previous research has shown that people walking on more difficult terrain display a decrease in speed of walking (Axelson and Chesney, 1999). The varying rates of travel in the pedestrian rate research suggest that these parameters contribute to the levels of difficulty of crossing certain types of terrain by foot. For example, a steeper uphill slows down the rate of travel, which indicates that this terrain is more difficult to cross, or certain types of vegetation such as grass are easier to cross than thick chaparral.

IMAGE CLASSIFICATION METHODS

There are numerous classification algorithms for remote sensing. Many approaches have been used with a range of success levels. These algorithms are generally divided into two categories: supervised and unsupervised. Supervised classification methods are initially more interactive than the unsupervised classification methods because the user chooses training data that will be used to assign each element, or pixels, to classes (Jensen, 2005). Unsupervised classification methods require less initial interaction with the user because the algorithm automatically identifies the clusters of from the dataset (Gonçalves, Netto, Costam and Zullo, 2008; Jensen, 2005). This is a good method for researchers with little *a priori* knowledge for classifying the data or for avoiding subjectivity in the classification process (Kelly, Shaardi, Guo and Liu, 2004). The unsupervised classification method was used in this study because little information of the clustering or classes was known prior to the classification process.

A commonly used algorithm for unsupervised classification is the K-means clustering algorithm. The objective of cluster analysis is for pixels that belong to the same class to have similar characteristics while pixels that belong to different classes have different characteristics so that differences between members of the same class are minimized, while differences between members of different classes are maximized (Gonçalves et al., 2008; Murray and Estivilli-Castro, 1998). To accomplish this, first, the number of clusters is determined by the user. Second, the cluster centers are initialized. Third, the means of the cluster are calculated and fourth, every element is assigned to the nearest cluster. Finally, the cluster means are recalculated. The last two steps are repeated until there is little or no change in the cluster means between the iterations (Vesanto and Alhoniemi, 2000).

K-means gained its popularity due to its ability to efficiently organize large datasets (Gonçalves et al., Kuo, Ho and Hu, 2002; Viswanathan, Pick and Hettrick, 2005; Huang, 1998). The K-means clustering technique is a discrete clustering method where each pixel is assigned a full membership to a cluster. However, this method may not always accurately represent the geographical world because in reality, each pixel is likely to belong to more than one class. The fuzzy K-means clustering method takes this into consideration and allows for a continuous approach to classification (Gorsevski, Gessler and Jankowski, 2003; Bezdek, Ehrlich and Full, 1982). In this method, a pixel can belong to more than one class as long as the membership value is between 0 and 1 and the sum of these membership values equal to 1 for each pixel (Jankowski, 2007). This method is more appropriate when classifying natural elements such as landforms or soil because these attributes are more continuous than discrete. Although other K-means clustering methods exist (e.g. extended K-means, agglomerative hierarchical, and fuzzy maximum likelihood) the fuzzy K-means clustering technique has been demonstrated to produce the most accurate results in reproducing the characteristics of input data (Duda and Canty, 2010). Thus, it has been a commonly used clustering algorithm applied to various application areas (Gorsevski et al., 2003).

One disadvantage of K-means clustering is that it needs user input for determining the number of clusters, and therefore assumes that this number is known prior to the process (Kuo et al., 2002; Gonçalves et al., 2008). To objectively determine the optimal number of classes, the classification algorithm can be repeated for a range of cluster numbers and the two parameters, the fuzzy performance index and the modified partition entropy are evaluated to minimize fuzziness of the classes (Burrough, Wilson, van Gaans and Hansen, 2001; Gorsevski et al., 2003). Another disadvantage of the K-means algorithm is that it can only work with numeric data or data where variables are measured on a ratio scale (Huang, 1998). This is a problem when working with categorical data, such as land cover. One method to overcome this issue is to reclassify the categorical data to an ordinal scale prior to using it as an input for the K-means clustering process (Wilkes & Jankowski, 2006).

There are algorithms that can handle categorical data as well as continuous data. The self-organizing map (SOM) is one such example. The SOM is a type of artificial neural network for the visualization of high dimensional data by orderly mapping the high dimensional data onto a low dimensional grid, thereby converting complex nonlinear relationships within the high dimensional data into low dimensional display (Kohonen, 1998). While doing so, the SOM preserves the topology and spatial distribution of the input space (Gonçalves et al., 2008). To accomplish this, the SOM has an input vector for each parameter that is connected to every output neuron by weights which are randomly assigned. Then, the Euclidean distances between the weight vector and input layer vector are calculated and the output layer neuron with the shortest distance is the winner. The weights of the winner neuron and its neighboring neurons are altered and the process is repeated until convergence is reached (Eastman, 2009). At this point, a feature map characterizing the distribution of input parameters using different colors for each class is generated.

SOM and K-means clustering are similar in multiple ways. First, both methods can utilize an unsupervised classification algorithm (Murtagh and Hernandez-Pajares, 1995). Second, SOM and K-means clustering result in an output grid where similar objects are closer to one another than dissimilar ones (Kohonen, 1998). And third, both methods can easily handle large amounts of data (Kuo et al., 2002). The major difference with fuzzy K-means is that in SOM, categorical data can be directly used as an input parameter and the number of output classes is automatically calculated. In addition, SOM preserves the topological features of the input datasets, meaning that patterns that are close in the input datasets will be mapped to areas that are also close in the output layer (Bação, Lobo and Painho, 2005). The most widely used SOM is Kohonen's algorithm (Kuo et al., 2002).

Researchers have been using SOM for the classification for remote sensing images because of its unique capabilities. To classify satellite imagery, it is common to first classify the image before integrating other GIS information. Using SOM, it is possible to include the GIS information at the initial classification stage. By doing so, dependency on training data can be reduced while increasing the initial accuracy level (Kamal, Passmore and Shepherd, 2010). The SOM has advantages over conventional methods of classification, such as maximum likelihood, Mahalanobis distance and minimum distance classification, which all assume that the input data is normally distributed (Kamal et al., 2010). Moreover, remote sensing data is not always parametric, so these methods may not be appropriate. In addition, these conventional methods require a large training sample to define a representative sample for the classifier. Finally, these methods do not take into consideration the topographic distribution of the data (Kamal et al., 2010). Kamal et al. found that when incorporating GIS information with SAR imagery, the SOM method produced the highest user's accuracy and producer's accuracy when compared with other conventional methods using the same amount of training data (2010). Although there are many GIS layers that could be integrated into the classification process such as but not limited to forest maps, soil maps, elevation and slope, the most effective GIS layers for classification are still unknown (Kamal et al., 2010). Currently, this process is conducted as supervised learning which means that training data is needed. Hence, the process is dependent on expert knowledge (Kamal et al., 2010). More research is needed to automate the classification process of satellite imagery. This advancement would decrease the amount of labor and be beneficial especially for applications with high data collection frequency or data analysis at regular intervals (Kamal et al., 2010).

The SOM has great potential to increase classification accuracy as well as to apply it to complex geographic information such as multi-band remote sensing imagery and GIS data. Because of its unique benefits, it has potential to be a useful alternative to more traditional methods of classification of remotely sensed images (Ji, 2000). There have been many studies that compare the K-means clustering technique with SOM algorithms without definite conclusion of which is better (Bação et al., 2005). More research needs to be conducted to maximize the advantages of SOM.

CHAPTER 4

RESEARCH DESIGN AND METHODS

The overall goal of this project was to identify areas with high porosity for pedestrians for potential future tourism development in the border region of Carinthia (Austria), Gorenjska, Savinusko, Koroska (Slovenia), and Friuli-Venezia Giulia (Italy). The project was divided into two parts. The first part was the classification of the border strip between Carinthia and Slovenia and Italy, based on topographic attributes, including land cover, elevation, and slope. The second part of the project incorporated infrastructure attributes such as roads, hiking trails, and mountain huts for a visual identification of high porosity areas.

STUDY AREA

The area in focus for this research project was the southern border of Carinthia that neighbors Slovenia and Italy on the Austrian side. The extent of analysis used was approximately 5 km north from this border into Carinthia, shown in Figure 1. This study area seemed suitable for the purpose of this research to locate areas with high porosity on the border.

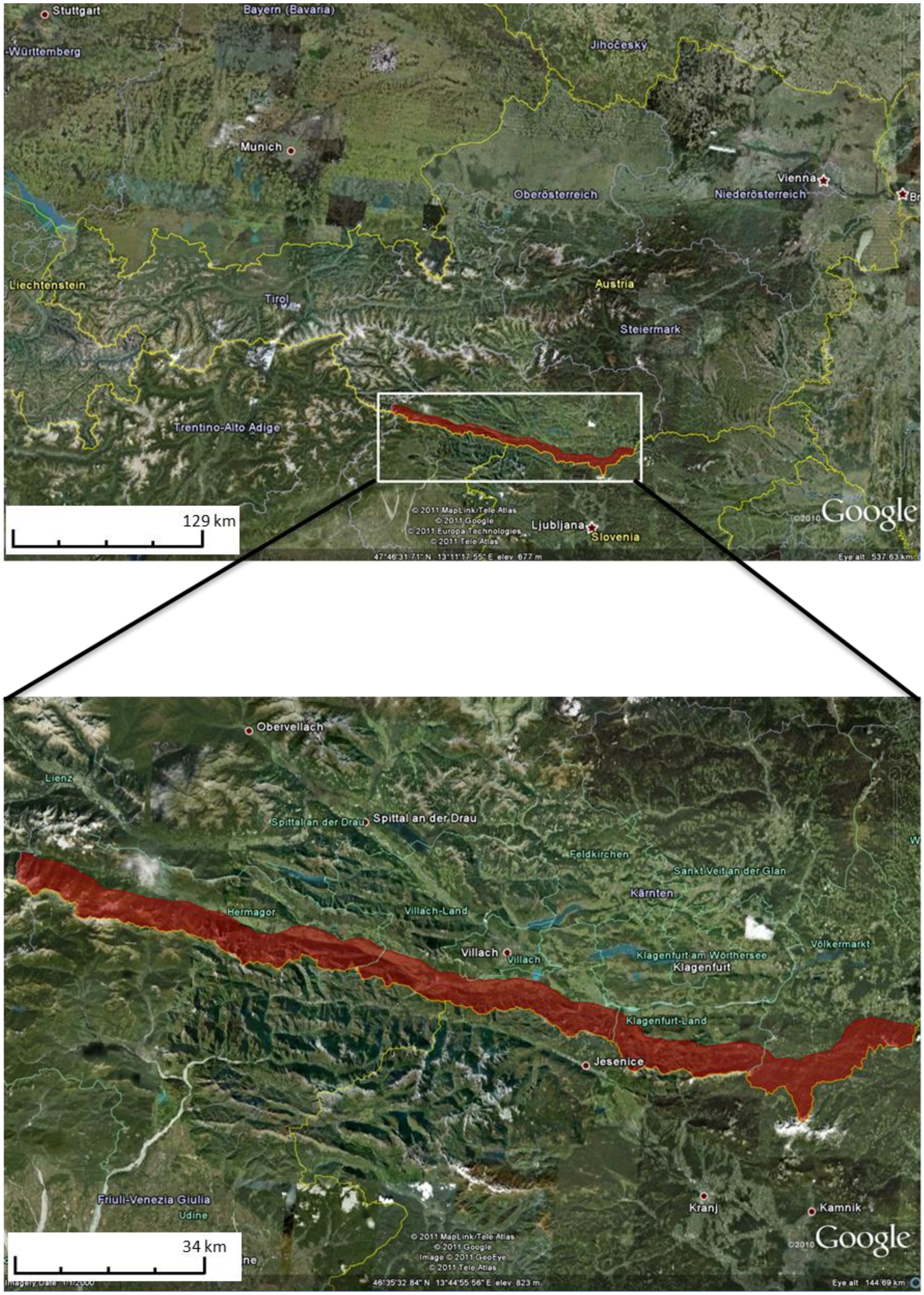


Figure 1. Study area of the southern border of Carinthia.

DATA ACQUISITION AND PREPARATION

Three input parameters relating to topographic features were used for this analysis: land cover, elevation, and slope. The two original datasets in this project were CORINE Land Cover data from the European Environment Agency and ASTER DEM elevation dataset. Slope was derived from the DEM elevation dataset. Additionally, mountain hut location data and roads and hiking trails data were obtained from the Provincial Government of Carinthia (Carinthia Geographical Information System KAGIS) for the second part of the analysis. The road data and hiking trails data were combined into one layer because a pedestrian can easily walk on either surface. Therefore, from here on, road data will refer to both roads and hiking trails.

The spatial data resolution used in the analysis was 100 meter. Initially, 25m resolution was tried but the processing times for 25m resolution datasets were significantly longer than the 100m resolution datasets. Therefore, 100m resolution was chosen as the practical resolution because it was large enough to retain the details of the data but small enough for processing time to be reasonable. The initial steps in data preparation were to aggregate the input datasets to 100m resolution and crop them to the extent of analysis. Then the datasets were processed using two clustering methods.

CONCEPTUAL ANALYSIS MODEL

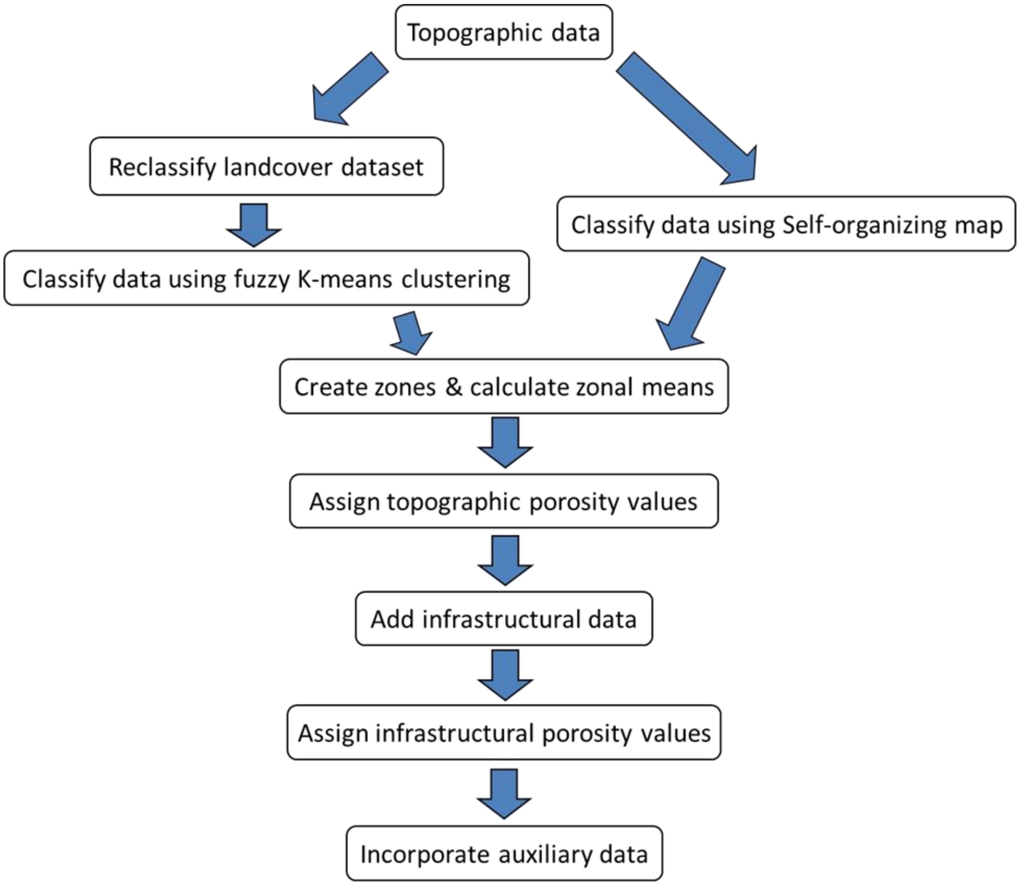


Figure 2. Workflow of the research project.

FUZZY K-MEANS CLUSTERING

The first method of clustering used was the fuzzy K-means clustering algorithm. The fuzzy K- means clustering can only handle continuous data. Because land cover data is categorical, it was reclassified into a continuous scale (shown in Table 1) before using it as an input in this algorithm:

1: No people are found in this area (e.g. open water)
2: People are very rarely found in this area (e.g. barren land or wetlands)
3: People are sometimes found in this area (e.g. forests, grassland)
4: People are often found in this area (e.g. developed open space, pasture/hay)
5: People are always found in this area (e.g. medium-high intensity developed)

Table 1. Land Cover Reclassification Table

Land Cover Reclassification		
Original Code	**Name of Land Cover**	**New Code**
111	Continuous urban fabric surfaces	5
112	Discontinuous urban fabric	5
121	Industrial or commercial units and transport units	5
122	Road and rail networks and associated land	5
131	Mineral extraction sites	4
133	Construction sites	4
211	Non-irrigated arable land areas	3
231	Pastures	3
242	Complex cultivation	3
243	Land principally occupied by agriculture, with significant areas of natural vegetation	3
311	Broad-leaved forest semi-natural	3
312	Coniferous forest areas	3
313	Mixed forest	3
321	Natural grassland vegetation association	2
322	Moors and heathland	2
332	Bare rock	2
333	Sparsely vegetated areas	2
411	Inland marshes	1
412	Peatbogs	2

Once the land cover was recoded, the fuzzy K-means algorithm was run using land cover, elevation, and slope as the input parameters. Because the optimal number of classes is initially unknown, to objectively find this number, the algorithm was run for a range of classes from 2 to 20. The number of classes that minimized the degree of fuzziness and the degree of disorganization which are measured by the fuzzy partition index and the modified partition entropy, respectively, was selected as the optimal number of classes. Next, the degree of fuzziness, or the phi value, which influences the level of hardness of the clustering, was determined. The phi value that maximized the objective function -dJ/dphi was used because this value provides the optimal balance between discontinuity and continuity (McBratney and Moore, 1985). To measure the similarity or dissimilarity of pixels and the similarity or dissimilarity of clusters, Mahalanobis distance was used because this method considers the correlations between variables (Gorsevski et al., 2008).

In fuzzy clustering, each pixel has the possibility to belong to more than one class. Accordingly, each pixel is characterized by a list of membership values representing the strength of membership in each class. For the purpose of classifying the border region only the highest membership value was retained for each pixel. Consequently, each class was constituted of those pixels, which attained the highest membership value for the given class.

SELF-ORGANIZING MAP (SOM)

One of the benefits of the SOM is that it can handle categorical data. Unlike the fuzzy K-means method, it was possible to directly use land cover, elevation, and slope as input parameters. The unsupervised SOM classification was used because the classes were initially unknown, and the maximum number of classes was set to 20. The K-means clustering method was used to assign pixels to the clustering after the initial SOM process. Integrating a clustering method with SOM has been found to perform better and require less computational effort relative to only using direct clustering (Vesanto and Alhoniemi, 2000). In this case, the SOM algorithm is first used to form prototypes of the classes, which generally have a larger number of clusters than expected. These prototypes are then further clustered using the K-means algorithm (Vesanto and Alhoniemi, 2000). The SOM output was a feature map of the classified border region, much like that of fuzzy K-means' result of mapping the maximum membership classes.

CREATING SEGMENTS FROM CLASSIFICATIONS

Both approaches (fuzzy K-means and SOM followed by fuzzy K-means) generated a representation of the border where each pixel belonged to a cluster, which was displayed using a different color. Although some trends were visible, in order to reveal the overall pattern of the border, the data was generalized to create homogeneous zones. To do so, the border classification was run through the focal majority function so that the value that appears the most often in the specified neighborhood appears in the output raster in the corresponding location. The output was a more generalized version of the border classification. The border region was manually edited to further generalize the classification where appropriate (i.e. small groups of pixels were merged with larger zones).

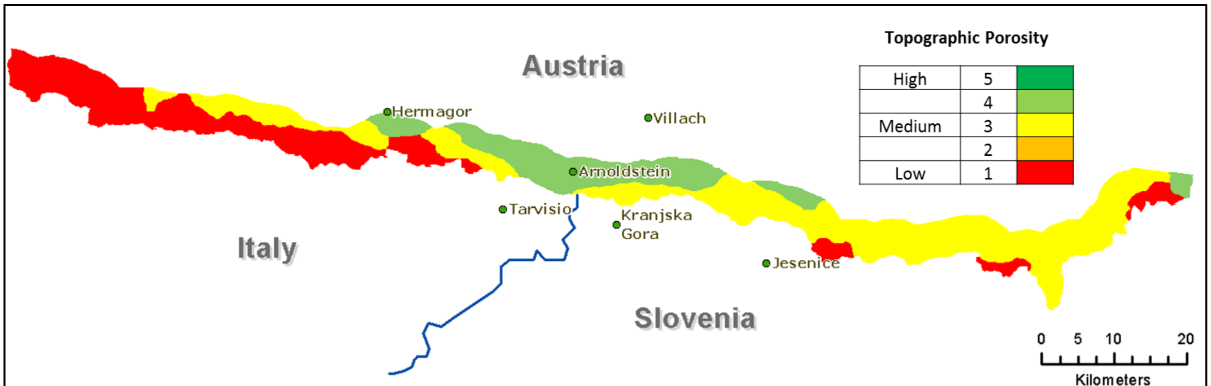
Once the zones were created, the summaries for each attribute for each class were calculated using the original 100m datasets for each parameter.

CHAPTER 5

RESULTS

Topographic porosity

Using 3-D visualization in Google Earth and the summary table of the attributes for the classes, a porosity value was assigned for each class for the results of both fuzzy K-means clustering (shown in Figure 3) and the self-organizing map (shown in Figure 4). This porosity includes land cover, elevation, and slope, and it is called "Topographic porosity." Because the land cover category "mixed forest" dominates most of the border strip and thus was the majority land cover for all the classes, elevation and slope were most influential in deciding the porosity values. Generally, the mean elevation and mean slope were positively correlated.



Class	1	2	3
Land cover (> 5%)	Mixed forest (49%), complex cultivation (16%), coniferous forest (10%), pastures (10%), discontinuous urban fabric (7%), non-irrigated arable land (6%)	Mixed forest (53%), coniferous forest (34%)	Coniferous forest (32%), natural grassland (23%), mixed forest (19%), moors & heathland (13%), sparsely vegetated areas (8%)
Mean elevation (m)	689.34	1131.51	1618.85
Mean slope (degrees)	12.21	28.05	29.76

Figure 3. Topographic porosity for fuzzy K-means clustering classification and its class summaries.

The first class has the lowest mean elevation and slope. This class is different from the other three classes because it is mainly characterized by land that is developed and used for farmland or residential areas. The land in this class includes some areas of hillsides with medium slopes but most of the areas are flat with low slope, which makes it very easy to cross. However, because it does have some altitude change and medium slope which may be somewhat of a struggle for some people, the topographic porosity of this class is 4.

Class 2 is characterized by mountain slopes. Because it generally does not include mountain peaks, it is easier to cross than class 3. However, this class does have steep slope throughout the zones that is comparable to that of class 3, which makes it difficult to cross. Therefore, the topographic porosity of class 2 is 3.

Class 3 consists of only the mountain tops of the border strip and does not include the base of the mountains; therefore, it has the highest mean elevation and slope of the three classes. Although the class does include some forested area, it also includes areas of little to bare vegetation which presumably is at the peaks of the mountains making it more challenging to cross. Moreover, traversing mountain peaks is extremely difficult and generally only can be done by experienced hikers or with proper gear. Therefore, the topographic porosity value for class 3 is 1.

Class	1	2	3	4
Land Cover (>5%)	Mixed forest (53%), complex cultivation (13%), coniferous forest (13%), pastures (8%)	Mixed forest (46%), coniferous forest (34%), moors & heathland (6%)	Coniferous forest (34%), natural grassland (29%), coniferous forest (20%), moors & heathland (7%), sparsely vegetated areas (5%)	Bare rock (29%), natural grassland (20%),mixed forest (16%), coniferous forest (11%), sparsely vegetated areas (11%), moors & heathland (9%)
Mean elevation(m)	782.20	1214.86	1566.16	1859.20
Mean slope (degrees)	15.09	27.53	30.80	37.65

Figure 4. Topographic porosity for SOM clustering classification and its class summaries.

Class 1 of the SOM classification is very similar to class 1 of the fuzzy K-means in terms of location of the areas and the attribute summaries. As stated in the fuzzy K-means section, this class consists mostly of flat areas with very little slope and therefore has a high topographic porosity of 4.

The land that belongs to class 2 has an overall higher mean elevation than land in class 1. This class includes steep mountain sides as well as some mountain peaks, which are generally challenging to traverse. The mountain peaks, however, are not as high compared with peaks in classes 3 and 4 and most of the land is covered with forests which are easier to walk through compared with other land types such as bare rock that is present in class 4. Class 2 has a topographic porosity value of 3.

Class 3 consists mostly of mountainous region and includes very little flat area. The mean slope is very steep and the mountain peaks of class 3 are higher than that of class 2; the mean altitude is higher also, which makes it more challenging to traverse the land. However, coniferous forests may provide for some traction on the ground as well as protection from exposure from natural elements (i.e. the sun), which makes the topographic porosity value of this class to be 2.

Class 4 occupies a very small area of the border strip and consists only of an area with very high slope and high altitude. Unlike the other three classes whose majority land cover is some type of forest, the dominating land cover for class four is bare rock. Walking on bare rock through high slopes and high elevation is extremely challenging and may not be possible for inexperienced walkers or without appropriate hiking gear. Although there are some forested areas present in this class, there are also some sparsely vegetated areas. These areas and areas of bare rock would provide very little protection from exposure to natural elements. Therefore, the topographic porosity of this class is very low at 1.

INFRASTRUCTURAL POROSITY

The road density and distance to nearest hut strongly influence the ability of a person to walk through the area. Regardless of topographic traits, roads will provide access to areas that are otherwise unreachable, and the presence of huts allows pedestrians to walk in areas that are very far from cities by providing a rest stop or a place to replenish their supplies. To view the distribution of both of these traits, road and hut distribution across the border strip were displayed. Road density data was processed with a kernel density function for improved interpretability. The result of this function was a more continuous raster image, much like a DEM, with a gradient that showed the distance from the nearest road. The values were then classified into three categories using Jenks natural breaks and the classes were labeled high, medium, and low road density. The hut distance data was also classified into three categories: 1000m from the nearest hut, 2000m from the nearest hut, and more than 2000m from the nearest hut. Because the pedestrian’s proximity to any road is imperative, only areas that are less than 50m from any road were used. For the hut distance data, areas up to 2000m of a hut were displayed. This map is displayed in Figure 5. Overlaying these two parameters, the infrastructural porosity was assigned, shown in Figure 6.

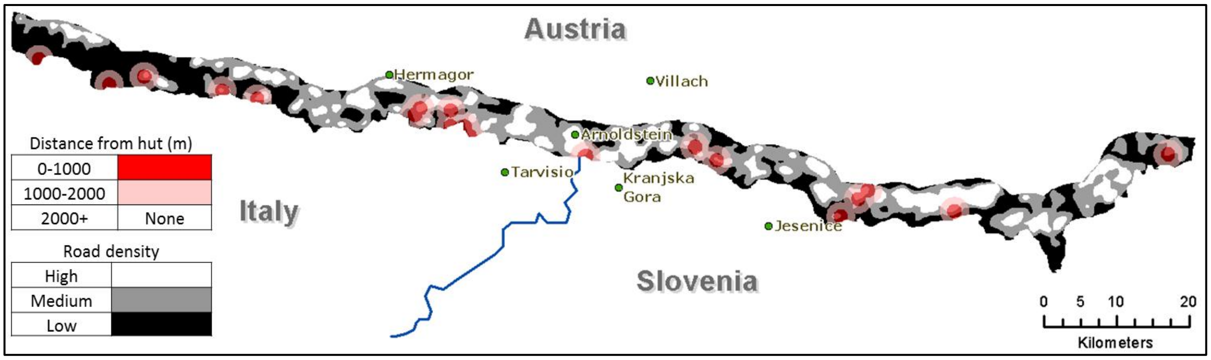
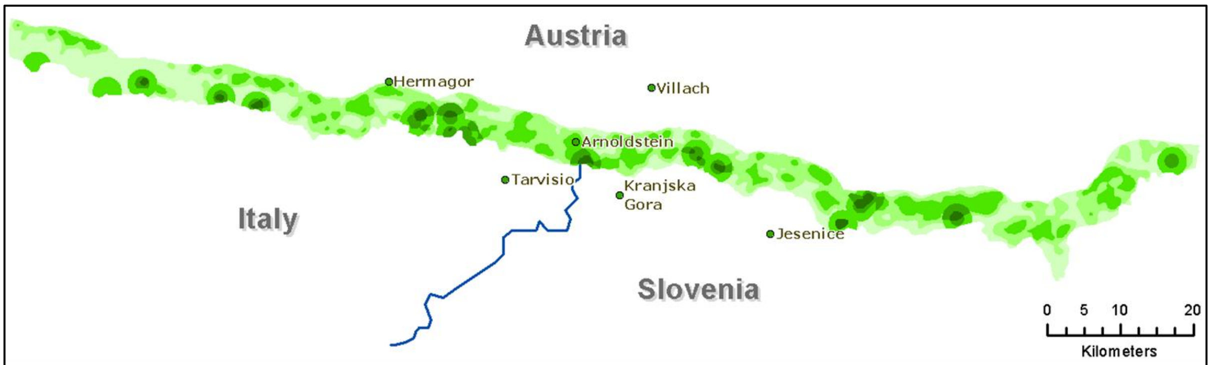


Figure 5. Visualization of infrastructure data (distance from nearest hut and road density).



Infrastructural Porosity			
High road density & within 1000m of a hut	5		High porosity
Medium road density & within 1000m of a hut OR high road density & within 1000m of a hut	4		
Medium road density & within 2000m of a hut OR high road density & 2000+ m from the nearest hut	3		Medium porosity
Medium road density & 2000+ m from the nearest hut OR low road density within 2000m of a hut	2		
Low road density & 2000+m from the nearest hut	1		Low porosity

Figure 6. Infrastructural porosity index.

Using this map, areas with porosity levels of 4 and 5 were combined to create a more generalized map of the locations of high porosity, shown in Figure 7.

Figure 7. The light green areas show the generalized areas with high porosity.

INCORPORATING AUXILIARY DATA

Because the study was conducted in Villach, Austria, the datasets provided covered only the Austrian side of the border. However, crossing the border involves countries on both sides of the border. Therefore, auxiliary data was used to compensate for the lack of data for the south side of the border and a schematic map was created (shown in Figure 8). The following four attributes were chosen to be displayed in the schematic map because each presence is likely to affect the flow of tourism traffic.

- *Major cities/towns:* major cities on both sides of the border need to be incorporated when considering border porosity because towns are generally the starting point and ending point providing resources such as housing, food, and rest areas in general. Fewer people are likely to cross border regions where there are no nearby towns on the other side. In addition, the flow of traffic to some of these towns may influence the number of people crossing the border.
- *Major ski resorts:* the resorts offer a place for sports such as skiing/snowboarding as well as lodges that serve as rest stops and provide food during the winter. In the summer, the ski resorts have a different appeal providing a base for numerous hiking routes around the mountains, funiculars for those just wanting to see the view, and other attractions such as the luge rides and dining. Because these activities can be enjoyed throughout the year, the existence of ski resorts most likely increases traffic flow in that region.
- *Major mountain summits:* in the Alps region of Austria, Italy, and Slovenia that is known for outdoor activities, hiking up mountains is a big attraction for tourists. When visitors are deciding where to go for a hike, mountains that are well known are a likely destination.
- *Roads that cross the border region in the north-south direction:* these roads that are mainly for vehicle traffic can have influence on pedestrians crossing the border. For example, the roads may increase accessibility of certain hiking trails. Or, the roads can contribute to improving certain infrastructure by the ability to supply them with certain goods, such as transporting food and water to huts. In other words, proximity to roads

makes building further infrastructure easier as well as encourages better management of the sites (Magablih and Al-Shorman, 2004).

Overall, the traffic flow of pedestrians is strongly influenced by the distance to scenic spots (Chen, Huancheng and Wang, 2009) which includes major ski resorts, major mountain summits and sometimes major cities/towns.

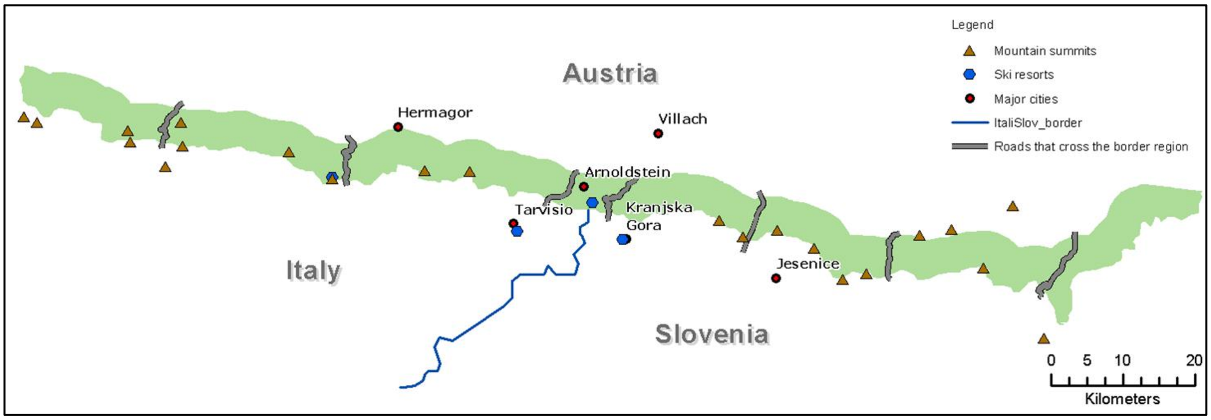


Figure 8. Schematic map representing the structure of the Carinthia border vicinity including major Points-of-interest and traffic connections.

CHAPTER 6

DISCUSSION

COMPARING THE RESULTS OF FUZZY K-MEANS CLUSTERING AND SOM

The patterns shown by segmentations resulting from both fuzzy K-means clustering method and self-organizing map method are visibly similar. Starting on the east side, both results have a small porous area of very similar attribute summaries. From there to about midpoint of the border region, both results have a medium porosity with a small area of high porosity. Then both results end up with a large area of low porosity on the western side of the border strip.

In general, the fuzzy K-means clustering analysis revealed areas with significant differences in porosity with higher granularity than SOM-based analysis. There are three major areas where this occurs. The first is to the east of Jesenice, where SOM uniformly classified as one class (and was given a porosity value of 3), fuzzy K-means clustering analysis revealed three areas of a different class towards the south end of the strip (which were given a porosity value of 1). When viewing this area in Google Earth’s 3D visualization, it shows that the three small areas of low porosity contain the highest peaks in the area, which makes it practical to separate these areas from the rest of the medium porosity areas. This area is shown in Figures 9 and 10 below.

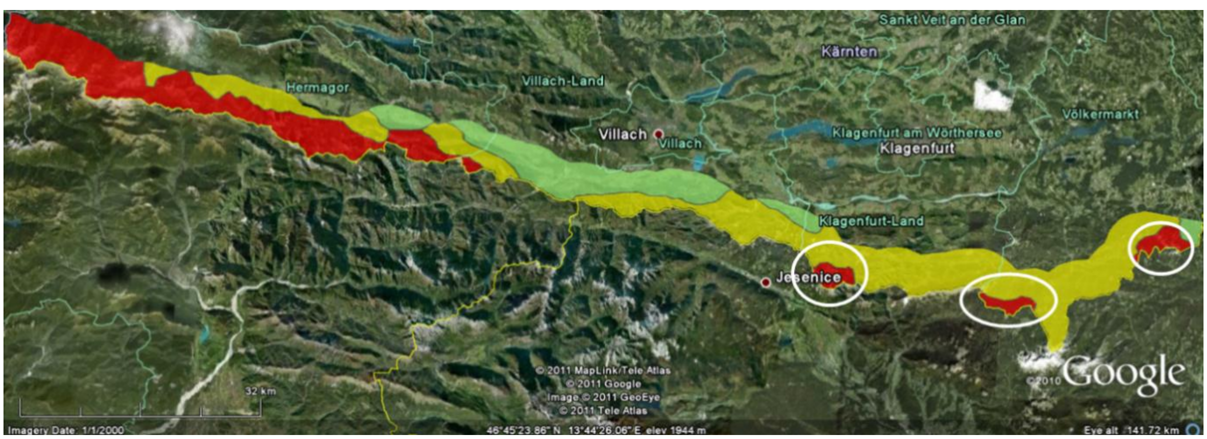


Figure 9. The three areas in fuzzy K-means clustering segmentation that do not exist in SOM result.

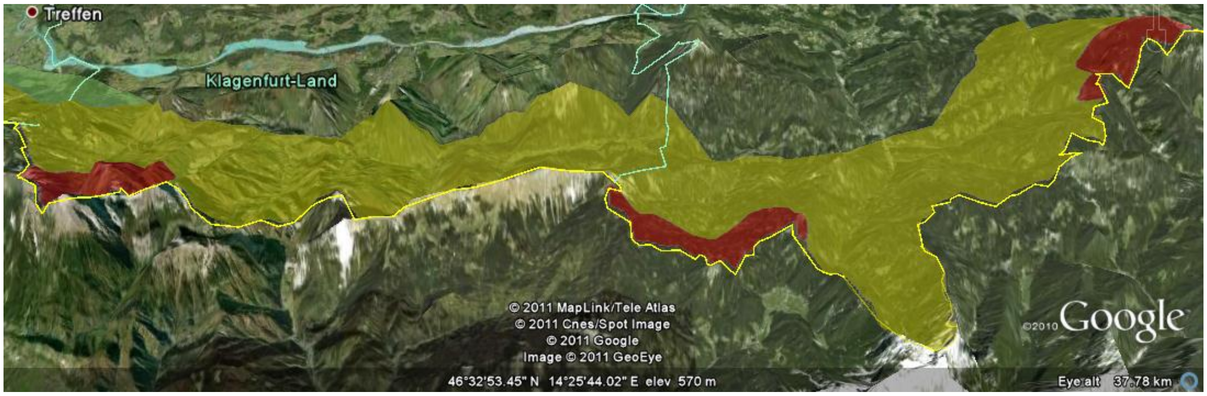


Figure 10. The three areas from fuzzy K-means clustering method zoomed in and displayed using 3D oblique view in Google Earth.

The second area where the results of the two classification methods differ can be seen near the center of the border region, between Hermagor and Villach. The high porosity area in the north is similar for both classification results. The difference is that SOM classifies the rest of the area as one class (which was assigned a medium porosity value) while the fuzzy K-means clustering method identifies a different class towards the southern area (which was classified as low porosity), shown in Figures 11 and 12. Visualization of this area in Google Earth 3D revealed that the low porosity sections are appropriate because they include the highest peaks within that area and thus have a much lower porosity than its surrounding regions.

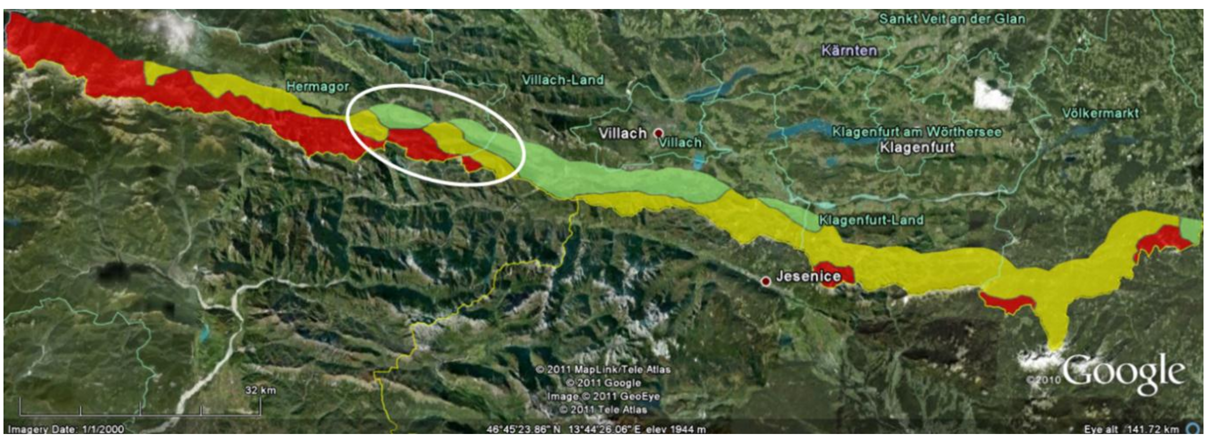


Figure 11. Area of low porosity from fuzzy K-means clustering that does not exist in SOM segmentation.

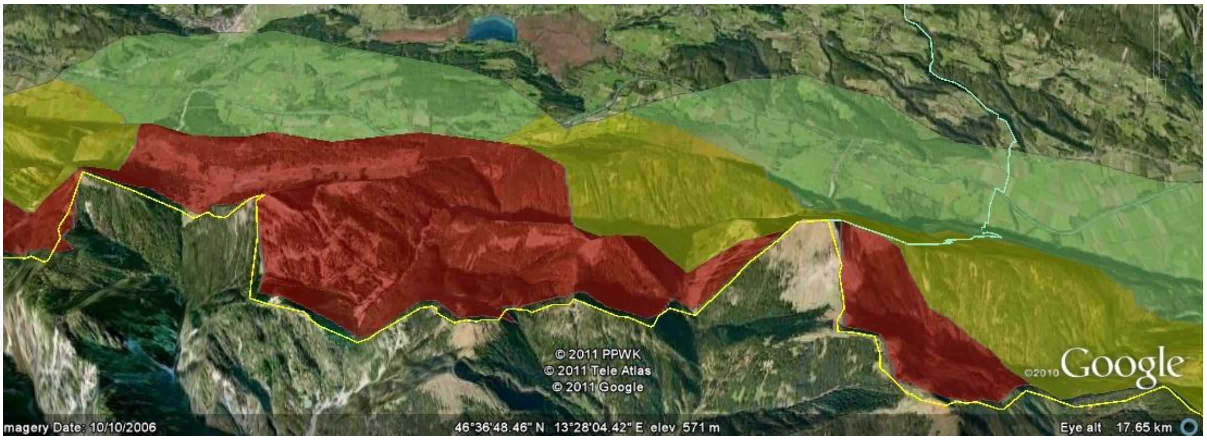


Figure 12. Low porosity area in fuzzy K-means clustering viewed using 3D oblique view in Google Earth.

The third area can be seen at the west end of the strip. SOM's classification shows the entire area to the west of Hermagor to be low porosity (porosity values 4 and 5). However, the fuzzy K-means clustering subdivides this area into medium and low porosity zones (porosity values 3 and 1, respectively). Although most of the west end is composed of high mountainous areas, there is a small area in the north of this part of the border that is flat, has lower elevation, and is used for agricultural or residential purposes. Because of this flat land, it seems that fuzzy K-means clustering split this area into two classes: the northern part including the developed area and the lower sides of the mountains while the southern part of this area is strictly mountains with higher elevation and slopes. This area is shown in Figures 13 and 14.

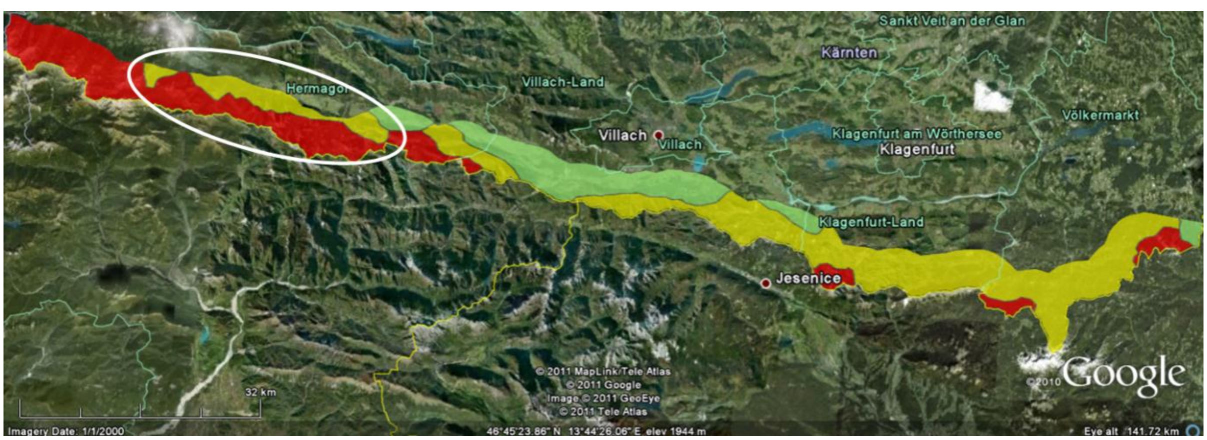


Figure 13. Medium porosity zone from fuzzy K-means clustering.

Figure 14. The medium porosity areas from fuzzy K-means clustering displayed in 3D using oblique view in Google Earth.

In contrast, SOM included the developed area with the mountainous area to create one class but created a different class within the region. This small area has the highest mean elevation and slope as well as a different land cover (i.e. bare rock as the dominant land cover instead of coniferous forest which is the dominant land cover of the surrounding region), which distinguishes this zone from its surrounding area. Although the two classes in question were assigned a different porosity value of 4 and 5, both of these values are on the low porosity end of the scale. Therefore, the small region may have different traits than its surrounding area but this distinction may serve little purpose because the porosity levels are very similar. This area is shown in Figures 15 and 16 below.

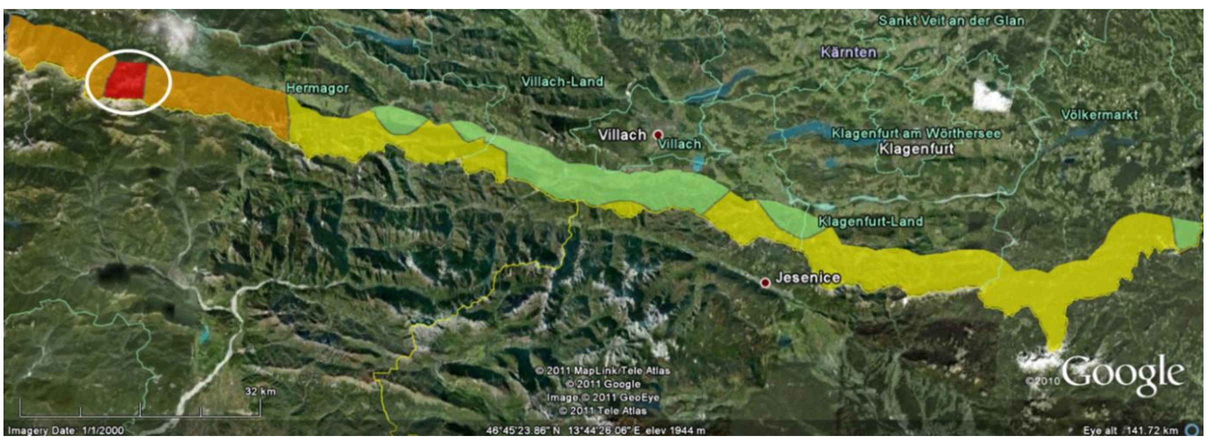


Figure 15. Low porosity zone resulting from SOM classification.

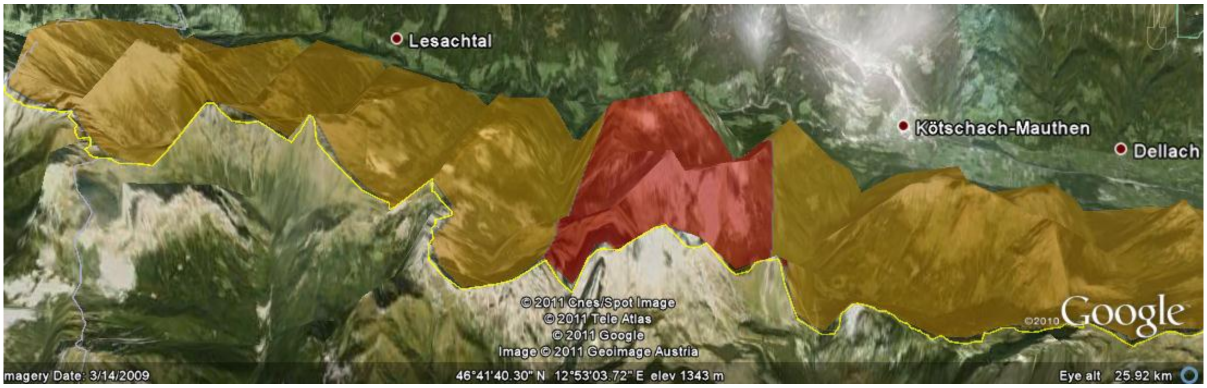


Figure 16. The low porosity area from SOM zoomed in and displayed using 3D oblique view in Google Earth.

As shown above, there are a few major differences between the results of the two methods of classification. All three areas where the differences are present show that the fuzzy K-means clustering method revealed areas whose porosity levels were notably different from its surrounding areas (i.e. medium level porosity vs. very low porosity). The third difference area shows the SOM made a distinction between low porosity and very low porosity. It seems that it is more important to detect areas whose difference is between medium to very low porosity than between low porosity to very low porosity. Therefore, the fuzzy K-means clustering method provides more useful information for the purpose of this study.

To further compare the two clustering methods, the mean road density and mean distance to nearest hut were calculated for each class for both results, and are shown in Tables 2 and 3.

Table 2. Class Summaries for Fuzzy K-means Classification

Fuzzy K-means clustering class summary			
Class	1	2	3
Road density (%)	5.93	5.52	3.53
Distance to hut (m)	4490.17	5208.96	4072.98

Table 3. Class Summaries for SOM Classification

SOM clustering class summary				
Class	1	2	3	4
Road density (%)	5.95	5.30	3.69	1.31
Distance to hut (m)	4542.17	5315.01	3689.28	2159.22

The mean road density and mean distance to nearest huts for both results were as predicted. The values for class 1 for both results are very similar and the road density is the highest because this class consists of developed land. Class 2 from fuzzy K-means clustering is similar to class 3 from SOM, and class 3 from fuzzy K-means clustering is similar to class 2 from SOM because they cover similar areas on the border. It is interesting to note that the distance to hut is the shortest in SOM's class 4, but this is mainly because the area of this class is very small.

LIMITATIONS OF THE ANALYSIS

It should be emphasized that the scope of this research project only includes the Austrian side of the border. Ideally, both sides of the border would have been analyzed for the border porosity index. However, data availability for the Italian and Slovenian sides of the border was an issue and only data for the state of Carinthia was obtained. Therefore, the porosity index that was developed is one-sided as it only applies to the northern side of the Austria – Italy – Slovenia border.

Due to the amount of time allotted for this project, only certain parameters were included in the analysis. However, there are additional parameters that could potentially affect porosity levels, such as the following:

- ***Seasonality.*** The porosity of a given area could drastically change depending on whether it is winter season or summer season in Carinthia. During the winter, ski mountaineering can increase porosity because it allows people to traverse parts of the mountain that are otherwise inaccessible without the snow cover or ski mountaineering gear. In contrast, the snow or ice cover can hinder pedestrians by making the roads less easy to use. Thus, in the summer, the presence of roads is highly influential in increasing porosity values but during the winter, it does not have the same effect. In addition, some huts are seasonally operated, meaning that they may be closed during the winter or the summer.
- ***The existence of alpine pastures***. During the summer, farmers take their cattle up to higher elevations to allow them to graze on the land. In this case, the farmer generally resides in a house up in the mountains. This contributes to increased porosity values in two ways. First, there is increased infrastructure because of the roads used by people and cattle. Second, these houses are sometimes opened up to hikers for use as a rest stop and a place to get food and/or water, much like the mountain huts.
- ***Surface curvature***. The surface curvature of the earth refers to whether it is ridge- or bowl-shaped. The porosity value of the region may vary according to the curvature. Similarly, the profile of the border strip may also be influential in the porosity of certain regions. For example, most people would not cross mountains at its highest peak but would prefer to walk through a mountain pass. Therefore, these factors can be used to locate smaller areas in the border with high or low porosity.
- ***Aspect***. The amount of sun varies according to which direction the slope is facing. This could mean that one side of the hill or mountain is hotter than the other, making it more difficult for crossing. This may not only determine the difficulty of the path but also the

time of day the hikers prefer to cross that particular area. In addition, the variation in the amount of sun contributes to differences in land cover. Certain types of vegetation grow better with a large amount of sun while others thrive in smaller amounts of sun. In some cases, the difference in land cover could affect the porosity of that area.

- ***Natural hazards***. Natural hazards are presented in this project as an auxiliary data in point format. However, a more detailed version of natural hazard data be used as one of the parameters to determine porosity because areas with high potential for natural hazards would decrease the porosity for that area.
- ***Wildlife protection zones***. Some areas of Carinthia are seasonally protected for wildlife, which would limit areas that the hikers can cross. For example, food is scarce for deer in Carinthia especially during the winter. To prevent the deer population from declining, there are areas where food is provided for them. Human disturbance in these areas could cause the deer to exert more than necessary energy to escape as well as to never return for food. Therefore, wildlife protection zones should be incorporated to identify which areas are inaccessible for pedestrians. Furthermore, if findings from this project are used to suggest areas for development for tourism or for increasing transport paths, identifying wildlife protection zones will be important because development in these areas should be avoided.
- ***Ownership of land***. Some of the mountainous land is privately owned. Although pedestrians are permitted to cross private land, bicyclists are not. Again, if there are plans for future development, ownership of land would be an obstacle to overcome.

FUTURE DIRECTION

Borders are traditionally thought of as lines that separate countries and states. However, due to the recent fluctuations of international borders, a shift in the border paradigm from the view of borders as something that separates to the view of borders as connecting links between countries can be observed. Border studies no longer only observe the physical border line but also include the social constructs of borders, border management, and how these newly created borders affect people’s lives (Newman, 2006a). Further, because of the historical mentality that borders represent separation, many border areas remain undeveloped. This provides for opportunities for development and new investment. The methods developed in this study can be applied to many of these analyses.

One specific potential application for this project is to use GIS for tourism. Although tourism planning is a popular field, using GIS in tourism studies is a relatively new concept (Magablih and Al-Shorman, 2004). Previously, tourism planning has been limited to identifying the location of certain infrastructure and explaining the reason for the location of such infrastructure (Boers and Cottrell, 2005). However, tourism planning tends to include complex spatial or geographical characteristics and simply identifying the location of such elements may not be enough (McAdam, 1999). GIS makes it possible to analyze tourism in a spatial context, which is crucial as tourism is essentially a spatial phenomenon (Boers and Cottrell, 2005). With

GIS, it is not only possible to identify the location of certain infrastructure but also to integrate other spatial components such as topological and thematic features all within a spatial context as well as work with both vector and raster data format (Boers and Cottrell, 2005). These datasets usually already exist or can be easily created within GIS, which decreases the cost and time of collecting data in the field (Chen et al., 2009). Having a decision making process grounded on an effective analysis system is important because the success of tourism industry essentially relies on the tourism industry's ability to develop, manage and market the tourism facilities (Jovanović and Njeguš, 2008).

To apply this project to tourism:

Step 1: conduct analysis at a smaller scale

This research was conducted at a regional scale of Carinthia. Future studies should use the findings from this project to determine which parts of the border region should be analyzed in a more detailed manner. For example, if identifying areas that should be developed for tourism, an area with a high number of attractions such as ski resorts and popular summits may be put in focus. From there, the following questions can be asked: Is there sufficient infrastructure to support the current flow of tourists? In what condition is the existing infrastructure? How can it be improved to better suit tourism needs? What are some actions to take to increase the flow of tourism in the area?

Step 2: consult experts in tourism

To make decisions about areas that should be recommended for potential future tourism development, people with extensive knowledge of tourism development should be consulted. Some questions to ask are: what are the specific criteria for a good tourism site? Are the attractions or accessibility to the attraction more influential in tourism? What is the influence of proximity to a city on tourism?

Step 3: decision support system

Using information of the border region and expertise of the tourism industry, a decision support system should be developed to determine the final recommendations for future tourism development. I.e. is it more beneficial to develop areas with many attractions with little existing infrastructure that is in a low porosity zone according to topography, or to expand or renovate areas with many attractions with high amount of infrastructure?

Step 4: incorporate sustainable tourism

After recommendations for future tourism development sites are produced, plans for sustainable tourism can be developed. Boers and Cottrell defines sustainable tourism as tourism that allows visitors to achieve expected experiences while meeting the carrying capacity standards and limiting resource impacts (2005).

CHAPTER 7

CONCLUSION

This research was conducted to develop a method to identify high porosity areas within the southern national border area of Carinthia, Austria. The results have shown that the fuzzy K-means classification is more effective than Self-organizing map-based classification. However, as previous research demonstrates that SOM can result in higher accuracy of classification, more research needs to be done to determine specific scenarios, in which these algorithms can be used optimally (Bação et al., 2005). Overall, the infrastructural porosity is more influential in determining the porosity value than topographic landscape because roads provide accessibility to areas that have very low topographic porosity. However, both types of information are useful for border studies. This project provided information on the border that could be further developed to assist in the decision making process of tourism or transportation development, and the methods developed for this project can be applied to other border studies.

REFERENCES

Association of European Border Regions (2010). *Aims and Tasks of AEBR*. 2010. Web. 20 Aug. 2011. <http://www.aebr.eu/en/profile/aims_tasks.php>

Axelson, P. and Chesney, D., 1999. Accessible Exterior Surfaces Technical Article. U.S. Architectural and Transportation Barriers Compliance Board, Washington, DC Contract #QA96005001.

Bação, F., Lobo, V. and Painho, M. (2005). Self-organizing maps as substitutes for K-Means Clustering.

Computation Science ICCS, 3516: 9-28. Doi: 10.1007/11428862_65.

Bezdek, J.C., Ehrlich, R., Full, W. 1982. FCM: The fuzzy c-means clustering algorithm. Computers & Geosciences. Vol. 10(2-3), pp. 191-203.

Boers, B, and Cottrell, S. (2005). Sustainable tourism infrastructure planning: a GIS based approach. In: Peden, John G.; Schuster, Rudy M., comps., eds. Proceedings of the 2005 northeastern recreation research symposium; 2005 April 10-12; Bolton Landing, NY. Gen. Tech. Rep. NE-341. Newtown Square, PA: U.S. Forest Service, Northeastern Research Station.

Brunet-Jailly, E. (2005). Theorizing Borders: An Interdiscirplinary Perspective. Geopolitics, 10: 633-649. Doi: 10.1080/14650040500318449.

Burrough, P., Wilson, J., van Gaans, P. and Hansen, A. (2001). Fuzzy k-means classification of topo-climatic data as an aid to forest mapping in the Greater Yellowstone Area, USA. Landscape Ecology, 16: 523-546.

Chen, N., Huancheng L., and Wang, L. (2009). A GIS-based approach for mapping direct use value of ecosystem services at a county scale: Management implications. *Ecological Economics*, 68: 2768-2776. Doi: : 10.1016/j.e colecon.2008.12.001

Coulter, L., Hisakawa, N., Jankowski, P. and Stow, D. (2010). Segmenting the Northern Border of the United States into Monitoring Zones. Department of Homeland Security, National Center for Border Security and Immigration, Project 1.7: Spatial-temporal patterns of smuggling and migration. Technical report, July 2010.

Diez, T., Stetter, S. and Albert, M. (2006). The European Union and Border Conflicts: The Transformative Power of Integration. *International Organization*, 60: 563-593. Doi:10.1017/S0020818306060218.

Duda, T. and Canty, M. (2002). Unsupervised classification of satellite imagery: choosing a good algorithm. *International Journal of Remote Sensing*, 23: 2193-2212.

Eastman, J.R. 2009. "SOM," IDRISI Help System. Accessed in IDRISI Taiga v16.05. Worcester, MA: Clark University.

European Commission (2001). *Unity, Solidarity, Diversity in Europe, its People and its Territory*; *Second report on economic and social cohesion European Commission*, 8 Sept 2011. Web. 20 Sept. 2011. <http://ec.europa.eu/regional_policy/sources/docoffic/official/reports/contentpdf_en.htm>

European Commission (2003) Tourism and the European Union (Brussels: European Commission). European Commission (2010a). *The EU Single Market: General policy framework*, 2 Dec. 2010. Web. 20 Aug. 2011. <http://ec.europa.eu/internal_market/top_layer/index_1_en.htm>

European Commission (2010b). *The EU Single Market: Living and working in the Single Market*, 21 Apr. 2010. Web. 20 Aug. 2011. <http://ec.europa.eu/internal_market/top_layer/index_15_en.htm>

European Union Regional Policy (2007). *Regions as partners: The European Territorial Cooperation Objective*,24 Dec. 2007. Web. 20 Aug. 2011. <http://ec.europa.eu/regional_policy/sources/docgener/panorama/pdf/mag24/mag24_en.pdf >

Gonçalves, M., Netto, M., Costam J., and Zullo J. Junior (2008). An unsupervised method of classifying remotely sensed images using Kohonen self-organizing maps and agglomerative hierarchical clustering methods. International Journal of Remote Sensing, 29(11): 3171-3207.

Gorsevski, P., Gessler, P. and Jankowski, P. (2003). Integrating a fuzzy *k*-means classification and a Bayesian approach for spatial prediction of landslide hazard. *Journal of Geographical Systems*, 5: 223-251. Doi: 10.1007/s10109-003-0113-0.

Huang, Z. (1998). Extensions to the k-Means Algorithm for Clustering Large Data Sets With Categorical Values. *Data Mining and Knowledge Discovery*, 2: 283-304.

Iron Curtain Consortium (2004). *Integrated multilayer database for the reference areas and interpreted maps and time series.* Project Reference No. QLK5-2001-01401. Accessed 20 Aug 2011. <http://www.geogr.uni-jena.de/fileadmin/Geoinformatik/c1stbe/ironcurtain/Publikationen/ra2_www.pdf>

Iron Curtain Consortium (2005). *Iron Curtain: Innovative models of critical key indicators…,* 30 June 2005. Web. 20 Aug. 2011. <http://www.geogr.uni-jena.de/4466.0.html?&L=2>

Jankowski, P. (2007). "A Rough Set-Based Approach to Handling Uncertainty in Geographic Data Classification," In: A. Moris and S. Kokhan (eds.), Geographic Uncertainty in Environmental Security. Springer Verlag, Berlin, pp. 75-87.

Jensen, J. (2005). *Introductory Digital Image Processing: A Remote Sensinf Perspective.* Upper Saddle River, NY: Prentice Hall.

Ji, C. (2000). Land-Use Classification of Remotely Sensed Data Using Kohonen Self-Organizing Feature Map Neural Networks. *Photogrammetric Engineering and Remote Sensing*, 66: 1451-1460.

Jovanović, V. and Njeguš, A. (2008). The Application of GIS and its components in tourism. *Yugoslav Journal of Operations Research*, 18(2): 261-272. Doi: 10.2298/YUJOR0802261J.

Kamal, M., Passmore, P. and Shepherd, I. (2010). Integration of geographic information system and RADARSAT synthetic aperture radar data using a self-organizing map network as compensation for real-time ground data in automatic image classification. *Journal of Applied Remote Sensing*, 4, 043534. Doi: 10.1117/1.3457166.

Kaiser, J. and Stow, S. (2007). Border Foot Trafficability Prediction Model. United States Border Patrol, San Diego sector and National Aeronautics and Space Administration.

Kelly, M., Shaardi, D., Guo, Q. and Liu, D. (2004). A comparison of standard and hybrid classifier methods for mapping hardwood mortality in areas affectged by 'sudden oak death.' *Photogrammetric Engineering and Remote Sensing*, 70: 1229-1239.

Kohonen, T. (1998). The self-organizing map. *Neurocomputing*, 21: 1-6.

Kuo, R., Ho, L. and Hu, C. (2002). Integration of self-organizing feature map and K-means algorithm for market segmentation. *Computers & Operations Research*, 29: 1475-1493.

Magablih, K. and Al-Shorman, A. (2003). Management and development of tourist sites in Jordan using Geographic Information System. *Information Technology & Tourism*, 6(4): 287-295.

McAdam, D. (1999): The Value and Scope of Geographical Information Systems in Tourism Management, *Journal of Sustainable Tourism*, 7:1, 77-92. Doi: 10.1080/09669589908667327.

McBratney, A. and Moore, A. (1985). Application of fuzzy sets to climatic classification. *Agricultural and Forest Meteorology*, 35:165–185

Minasny, B. and McBratney A. (2000). FuzME version 2.1. Australian Centre for Precision Agriculture, The University of Sydney. Accessed 13 June 2011, http://www.usyd.edu/au/su/agric/acpa.

Murray, A. and Estivill-Castro, V. (1998). Cluster discovery techniques for exploratory spatial data analysis. *Int. J. Geographical Information Science*, 12:5(431-443).

Murtagh, F. and Hernandez-Pajares, M. (1995). The Kohonen Self-Organizing Map Method: an Assessment. *Journal of Classification*, 12: 165-190.

Newman, D. (2006a). Borders and Bordering: Towards an Interdisciplinary Dialogue. *European Journal of Social Theory*, 9: 171. Doi: 10.1177/1368431006063331.

Newman, D. (2006b). The lines that continue to separate us: borders in our 'borderless' world. *Progress in Human Geography*, 30(2): 143-161.

Star, H. (2000). Opportunity, willingness and geographic information systems (GIS): reconceptualizing borders in international relations. Paper prepared for the conference, "New Methodologies for the Social Sciences: The Development and Application of Spatial Analysis for Political Methodology," Institute of Behavioral Sciences, University of Colorado, Boulder, Colorado, March 10-12, 2000

Stephenne, N. and Zeug, G. (2007). Border permeability modeling: technical specifications at global and local scale. OPOCE (Publ.), Luxembourg - JRC42333.

Vesanto, J. and Alhoniemi, E. (2000). Clustering of the Self-Organizing Map. *IEEE Transactions on Neural Networks*, 11(3): 586-600.

Viswanathan, N., Pick, J, and Hettrick, W. (2005). An analysis of commonality in the twin metropolitan areas of San Diego, California, and Tijuana, Mexico. Socio-Economic Planning Sciences, 39(57-79).

Wilkes, M. and Jankowski, P. (2006). “Diving the border into homogeneous segments: a step by step description.” Department of Homeland Security, Center for Border Security and Immigration. Technical Report, July 2006.