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Spatial Information Management

MASTER'S THESIS

Assessment and Evaluation of Urban Blight applying Geospatial Technology

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Abstract

GIScience methods play an important role in spatial crime analysis. Research shows that crime in urban areas is not homogeneously distributed, but it is clustered in so-called “hotspots”. The key to reducing crime rates is to focus on micro units of places to allow researchers to understand factors that lead to crime. The Broken Windows Theory suggests that areas where broken windows are concentrated attract criminal activities with fear of crime in these areas increasing. Broken windows are only one of many visual indicators of urban blight, which describes the disorder of properties and environment in urban areas. The issue of blight and its correlation with criminal incidents have been subject to great debate, however there is a need for more detailed fine-scale data collection to observe urban neighborhood characteristics. The primary goal of this work is to apply a mixed-methods approach, including spatial video, geo-narratives, and skin-conductive wristbands to explore urban blight and its correlation with crime rates, and to identify high fear areas of crime depending on environmental characteristics. The analysis is carried out at a micro level in the city of Baton Rouge, Louisiana, one of the most violent and dangerous cities in the United States. A standardized method is required to collect and process contextual data, so that results can be used for long-term research and comparative studies. Qualitative and quantitative data are collected in selected neighborhoods with a high, medium, and low crime density. Urban blight indicators and people’s subjective perceptions of crime are extracted from recordings of test subjects and implemented into a GIS-based model. Benefits and limitations of such technologies are studied in detail. Clustering methods, spatial (auto) correlation, and interpolation techniques are carried out to investigate relationships between visual urban blight and crime data. Text-mining techniques such as self-organizing neural networks are used to explore subjective perceptions of crime. Results indicate that there is a positive significant correlation between urban blight and crime, and that people tend to feel less safe in areas where blighted buildings are concentrated. The new methodological approach opens up new opportunities to use GIS in mixed-methods research and allows a new perspective on understanding the occurrence of crime patterns. The proposed methodology can be applied in a wide range of research fields to assess fine-scale environmental characteristics and human behavior over geographic space and time.

Keywords: urban blight, crime perceptions, spatial crime analysis, spatial video, geo-narratives, GIS

Kurzfassung

Geoinfomationssysteme spielen eine wichtige Rolle in der räumlichen Kriminalitätsanalyse. Aktuelle Forschungsergebnisse zeigen, dass Kriminalität nicht homogen verteilt ist, sondern sich auf bestimmte Bereiche – sogenannte „Hot Spots“ - konzentriert. Gemäß der „Broken Windows Theorie“ können Anzeichen von Verwahrlosung wie zerbrochene Fenster, Graffiti oder Müll in einem Stadtviertel kriminelle Aktivitäten anziehen, und nimmt die Angst für Kriminalität zu. Die Thematik des Stadtverfalls (Engl. „Urban blight“) und der Zusammenhang mit Kriminalität wird häufig diskutiert und bedarf einer genaueren Datenerhebung. Ziel dieses Projekts ist es, neue interdisziplinäre Forschungsmethoden anzuwenden, um den städtischen Verfall und den Zusammenhang mit Kriminalitätsraten und Kriminalitätswahrnehmung auf einer Mikroebene in der Stadt Baton Rouge im US Bundesstaat Louisiana zu untersuchen. Nach offiziellen Angaben des Straftatbestandes vom FBI wird Baton Rouge als eine der gewaltsamsten und gefährlichsten Städte der Vereinigten Staaten eingestuft. Innovative Geoinformationstechnologien wie „Spatial Video Technology“, „Geo-Narratives“ und „Sensor-Armbänder" sollen dabei helfen, Faktoren die zu hohen Kriminalitätsraten führen, zu identifizieren. Standardisierte Methoden sind erforderlich, um raumbezogene Daten zu erheben, zu verarbeiten und zu analysieren, damit die Ergebnisse für Langzeitforschung genutzt werden können. Qualitative und quantitative Daten werden in ausgewählten Nachbarschaften mit hohen, mittleren und niedrigen Kriminalitätsraten erfasst. Aus den gesammelten Daten werden Indikatoren für Stadtverfall und subjektive Kriminalitätswahrnehmung von Individuen extrahiert und in einem GIS-basierten Modell umgesetzt. Clustering-Methoden, räumliche (Auto)korrelation und Interpolationstechniken werden durchgeführt, um die Zusammenhänge zwischen visuellem Stadtverfall und tatsächlichen Kriminalitätsdaten zu untersuchen. Text-mining Techniken wie „self-organizing neural networks“ werden eingesetzt, um subjektive Wahrnehmungen von Kriminalität zu erforschen. Die Ergebnisse deuten darauf hin, dass es einen positiven signifikanten Zusammenhang zwischen Stadtverfall und Kriminalität gibt. Dieser innovative „mixed methods“ Forschungsansatz erlaubt eine völlig neue Sichtweise kriminalitätsbezogene Faktoren besser zu verstehen. Die vorgeschlagene Methodik kann in einem breiten Spektrum von Forschungsbereichen angewendet werden, um feinskalige Umweltmerkmale und menschliches Verhalten über Raum und Zeit zu bewerten.

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List of Abbreviations

BR	Baton Rouge
BRPD	Baton Rouge Police Department
EBRP	East Baton Rouge Parish
ERD	Entity-Relationship Diagram
GIS	Geographical Information Systems
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
GSV	Google Street View
HD	High Definition
KDE	Kernel Density Estimation
LSU	Louisiana State University
NIJ	National Institute of Justice
NNA	Nearest Neighbor Analysis
NNI	Nearest Neighbor Index
OSM	Open Street Map
SSO	Systematic Social Observation
SV	Spatial Video
SVAS	Spatial Video Acquisition System
SVG	Spatial Video Geo-narrative
UAV	Unmanned Aerial Vehicle
UCR	Uniform Crime Reporting

Chapter 1

1 Introduction

According to law enforcement authorities (National Institute of Justice 2013) GIScience methods play an important role in identifying factors that contribute to crime and in understanding crime patterns from a geographic perspective (Chainey and Ratcliffe 2005). A geographic information system (GIS) is an effective problem solving tool for capturing, manipulating, storing, analyzing, and visualizing all types of spatial data in a wide range of application fields (Longley et al. 2015). This thesis focuses on the issue of urban blight, which describes disordered neighborhoods in urban areas characterized by deterioration of properties and environment, for example abandoned cars, barred windows, dumping, graffiti, infrastructural degradation, overgrowth, etc., and by social and economic problems. The issue of urban blight also referred to by the *Broken Windows Theory* is introduced by Kelling and Wilson (1982). In addition to property and environmental decay in specific urban neighborhoods, a key part of this theory is the fear of crime. Through disorder in neighborhoods, it is likely that certain groups of people become fearful and withdraw from the community, what results in a rise of disorder and criminal activities in these areas.

1.1 Problem statement and Goals

Research shows that crime is not homogeneously distributed across cities but is clustered in so-called hotspots. The key to reducing crime rates is to focus on micro units of place to allow researchers to understand factors that lead to crime. The issue of urban blight and its correlation with criminal incidents has been subject to great debate, however there is a need for more detailed fine-scale data collection to observe urban neighborhood characteristics and to include qualitative data to understand people's perceptions and experiences in specific areas (Hinkle and Weisburd 2008). A common method to determine urban blight and crime perception is through observation surveys. Moreover, Google Street View has been used to observe the environment and to study neighborhood disorder (Marco et al. 2017; Curtis et al. 2013c).

The primary goal of this work is to apply a newly developed mixed-methods approach to explore physical urban blight and its relationship with reported crime and crime perception at a micro level. Qualitative and quantitative data are collected in selected neighborhoods with a high, medium, and low crime density. A standardized method is required to collect and process the acquired contextual data, so that results can be used for long-term research and comparative studies. Up to now, no such standardization exists.

The city of Baton Rouge, LA, is chosen as appropriate study area. According to data from the FBI's Uniform Crime Reports, Baton Rouge is ranked as one of the most violent and dangerous cities in the United States (Kaplan 2019). The city receives aid from the US Department of Justice to try to reduce violent crime. In order to conduct effective crime prevention strategies, methods that study crime patterns have to be developed in order to propose long-term plans to reduce crime rates.

1.2 Research questions

This research aims to answer the following three research questions:

I. *How can innovative geospatial technologies, like spatial video and geo-narrative, be effectively used to identify physical urban blight types and to measure individual's perception of crime?*
II. *What kind of relationship exists between physical urban blight and crime in Baton Rouge?*
III. *What factors influence subjective perceptions of crime in Baton Rouge?*

1.3 Approach

This research evaluates new geospatial technologies, including spatial video, geo-narrative, and skin-conductive wristbands, to identify physical urban blight in Baton Rouge and its correlation with objective (officially reported) crime and subjectively perceived crime.

Reported crime data and additional information are collected from official open data sources. Spatial video technology is used to collect urban blight data. Neighborhoods with a high, medium, and low crime density are selected and routes through these neighborhoods covering all streets are

designed for data acquisition. Five cameras are attached to the inside windows of the car recording videos of the area that is driven through. Urban blight indicators are extracted from the video recordings. A standardization of urban blight indicators is required in order to quantify the physical quality and the level of blight at an appropriate spatial unit. A criteria catalogue for mapping urban blight is developed to ensure consistency in the analysis. Urban blight indicators are aggregated through spatial statistical analysis into an urban blight index in order to conduct standardized analysis. Additionally, geo-narratives and skin-conductive wristbands are used to collect empirical and physiological data. These data are used to extract information about people's perception of crime. The environment along the selected routes is used to stimulate a discussion/interview with experts, students, and local stakeholders. Each recorded frame of the spatial video, geo-narrative, and skin-conductive wristbands contains information about its geographical location and possesses a timestamp, which makes spatio-temporal analysis possible. This geospatial technology allows acquiring data on a fine-scale level. At the same time, the test subject is equipped with a skin-conductive wristband that contains high quality sensors for measuring physiological parameters to determine individual emotions and moments of stress. However, little research has been done on the additional benefit of physiological sensors for safety perception. The interpretation of the acquired physiological data require expert's interpretation. Therefore, while data collection with skin-conductive wristbands has been implemented in this research, analysis of the collected data will be conducted in future research, working together with experts in this research field.

Clustering methods, spatial (auto) correlation, and interpolation techniques are implemented in a GIS-based model to investigate spatial patterns of urban blight and to analyze relationships between visual urban blight and crime data. Text-mining techniques such as self-organizing neural networks are used to explore subjective perceptions of crime.

1.4 Audience

In general, crime can influence life quality in urban neighborhoods. City institutions and police departments are interested in finding solutions of how to effectively prevent and predict crime. Crime maps help city authorities to better understand the occurrence of crime and crime-related factors to reduce crime rates and to improve public safety. Spatial crime patterns help spatial planning departments to develop a safe and secure urban environment to increase the life quality.

Directed investments based on spatial crime patterns may lead to more wealth in urban neighborhoods (National Institute of Justice 2013, 2018). Local inhabitants are also an audience, who benefit from spatial planning and security improvements made by local authorities and governmental institutions. Subsequently the prevention of crime supports communities as the percentage of thefts, burglaries, robberies, homicides etc. are reduced. Finally, academic experts and researchers may also be interested in this research, because new geospatial technologies can be used as a new approach in a wide field of environmental studies.

1.5 Thesis structure

This thesis is structured as follows. The literature review in Chapter 2 provides background material for this thesis by reviewing relevant crime concepts, such as the Broken Windows Theory, the fear of crime, and the urban blight concept. Moreover, geospatial technologies (i.e. spatial video and geo-narrative) are introduced and described with examples in various application fields. The last section of the literature review gives an overview of traditional and state-of-the-art methods that are applied to measure urban blight in general, and in Baton Rouge, specifically. Chapter 3 defines the conceptual framework and project requirements, including criteria catalogues for crime and urban blight, in order to implement and analyze study results. Chapter 4 outlines the workflow for the methodological approach, where the methods and techniques for data acquisition, data processing, data analysis, and data visualization are described. In Chapter 5 the selected study area, data sources, and the implementation of technologies are presented. This is followed by the analysis of results in Chapter 6. The discussion section in Chapter 7 interprets the results based on the research questions and discusses benefits and limitations of the employed methodology. Chapter 8 summarizes the approach and findings and discusses potential future research and development opportunities. Finally, the appendices contain (a) examples of photographs of urban blight indicators defined in the criteria catalogue, and (b) the background questionnaire with respect to safety perception in the city of Baton Rouge.

Chapter 2

2 Literature review

This chapter provides an overview of relevant criminological concepts that address the relationship between crime and urban blight. Moreover, possible applications of geospatial technologies, in particular spatial video and geo-narrative, are described. The last section of Chapter 2 presents traditional approaches and state-of-the-art methods to measure urban blight and the relationship to crime.

2.1 Crime concepts

In general, researchers from different academic disciplines such as health, sociology, psychology, geography, or criminology are interested in theories that identify important neighborhood and community characteristics. Different concepts that describe neighborhood disorder regarding objective and subjective characteristics of crime are described below, where objective crime indicators include data and statistics from official crime reports and subjective crime indicates the individual's perception of crime in specific neighborhoods, such as the level of safety or the fear of crime (van Bakergem et al. 2017; Ross and Mirowsky 2001).

2.1.1 The Broken Windows Theory

The Broken Windows Theory is an important theory in criminology, first introduced in *The Atlantic Monthly* magazine by the two social scientists George L. Kelling and James Q. Wilson (1982). In this article the authors argue that factors such as broken windows, high-grown weeds, or graffiti indicate disorder in urban neighborhoods. Broken windows send a signal of lack of enforcement and community control leading to an increase of crime rates. It is likely that if one broken window appears, there will be more broken windows within a short period of time within the same area. Even in well-functioning neighborhoods a small violation can lead to social disorder. Social norms are no longer respected, violence starts to increase, and the fear of crime in the once decent neighborhood rises. People's behavior starts to change, because residents perceive a rise in violence.

A certain group of residents does not feel safe anymore and moves away, others get more rowdy and violent, start drinking on the streets, and litter on the streets starts to accumulate. This results in the increase of fear among citizens, and people start avoiding public places (Kelling and Wilson 1982). The above described chain of events occurring when disorder is unobserved, is shown in Figure 1.

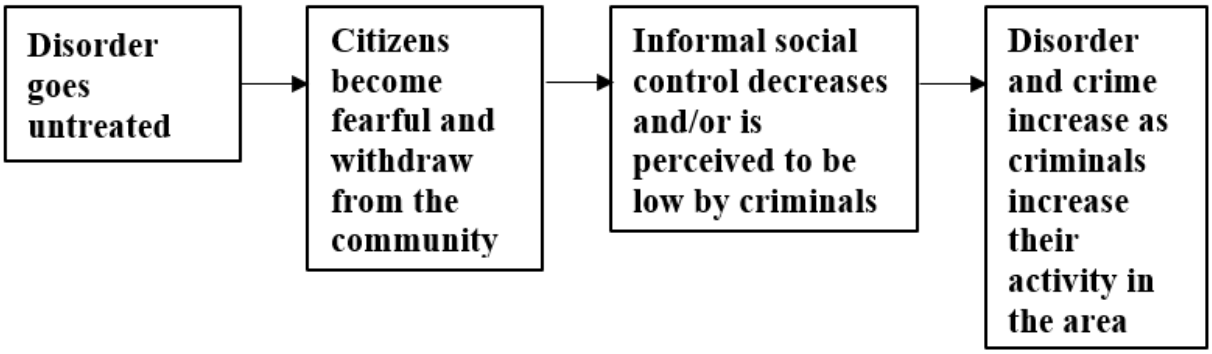

Figure 1. Broken windows effect (Hinkle and Weisburd 2008)

The Broken Windows Theory became important in urban policing strategies, also known as broken windows policing. Police officers were sent to streets in disordered neighborhoods to observe and control. These actions to control public incivilities have influenced many disordered neighborhoods in major U.S. cities in a positive way (Sampson and Raudenbush 1999).

The Broken Windows Theory is an underlying basis for the urban blight concept, described in the next section 2.1.2, which is relevant in order to implement this study.

2.1.2 Concept of urban blight

Kelling and Wilson (1982) mention in their Broken Windows article the term “urban decay”. Urban decay is a synonym for “urban blight”. In this paragraph different definitions and characteristics of blight that have been developed over the years are described.

The etymology of “blight” dates back to the 16th century, originally used by farmers as a term for a disease of plants or nature (Oxford dictionaries 2019). Since the 1970’s studies have focused on the concept of urban blight to describe disorder in neighborhoods. Research indicates that urban blight occurs in areas with high rates of poverty, crime, minority households and slums (Maghelal

et al. 2013). In general, many studies make a distinction between social and physical disorder/blight. Authors refer with social urban blight to the anti-social behavior of mostly unpredictable people. This can include for example verbal harassment in public places, open solicitation for prostitution, school truancy, public urination, people sleeping in public, nuisance neighbors, etc. (Sampson and Raudenbush 1999; Skogan 1990; Kelling and Wilson 1982). Physical urban blight on the other hand, is described as the deterioration of urban landscapes. This includes for instance abandoned properties, abandoned or burned-out cars, broken windows, broken streetlights, overgrown vegetation, illegal dumping, graffiti, etc. Physical urban blight triggers bigger visible damage than social urban blight. Social urban blight on the contrary, occurs more frequently but the damage is not as obvious (Skogan 2012; Kelling and Wilson 1982).

Although a distinction between social and physical urban blight can be made, the line of separation is not always clear. Over the years the definition of the urban blight concept has changed from considering mostly physical factors to additionally integrating subjective factors. Social and physical urban blight as well as socio-economic factors are relevant measures to assess and understand neighborhood disorder in urban areas (Skogan 1990; Hinkle and Weisburd 2008).

2.1.3 Fear of crime

Wilson and Kelling (1982) hypothesized that a lack of social control in disordered neighborhoods increases the fear of crime. Primarily, people are afraid of getting involved in a violent attack. Another source of fear is the harassment of unpredictable strangers with untended behavior like drunks, prostitutes, rowdy teenagers, loiterers, etc., who are not necessarily criminals. Certain people do not feel safe anymore, resulting in avoidance of public places, as people prefer to stay in their houses or avoid driving through these areas. Others move away from their neighborhood. This turns into another increase of urban blight and crime rates, since there is less social observation.

Sampson and Raudenbush (2001) found that in neighborhoods where the cohesion among residents and the social observation of police officers is high, the rate of violence is low. The authors also stated that physical and social disorder decrease when the cohesion among residents (collective efficacy) is strong. Several studies show that police presence in disordered neighborhoods can also have a negative influence on the community. Although the observation of police officers aims to discourage criminals to commit a crime and to make a neighborhood safer, residents may become

more fearful towards the police presence. This does not apply to people commuting through these areas, but more to citizens who observe street behavior from their homes (Weisburd et al. 2010). Disorder triggers negative perceptions in people's minds, which influences, for example, the real estate market. People are not willing to buy houses in affected areas, and investments will be stopped (Sampson and Raudenbush 2001). Ross and Mirowsky (2001) found in their study that perceived neighborhood disorder can influence the health of residents. They tend to have more physical impairments and chronical health problems.

2.1.4 Discussion in the literature of crime concepts

The Broken Windows Theory hypothesis states that there is a correlation between disorder and crime. This hypothesis has been tested and discussed in several studies over the years. The supporters and critics of the Broken Windows Theory and the different concepts of urban blight are presented in this paragraph.

Sampson and Raudenbush (1999) applied the systematic social observation method to observe disorder in urban neighborhoods. The authors concluded that disorder does not immediately cause crime, although crime and disorder are related. They found that there is a direct link between disorder and certain types of crime (i.e. robbery), however homicides for example do not correlate with disorder. The authors also stated that robbery rates decreased, when there is social observation in the neighborhood. Moreover, the systematic social observation study revealed that sociodemographic characteristics, such as poverty or type of land use, affect the level of disorder.

Other researchers stated that also the fear of crime has to be taken into account in order to assess urban blight. Hinkle and Weisburd (2008) determined in their study that disorder influences the fear of crime. This statement confirms the Broken Windows hypothesis that there is a relationship between disorder and the fear of crime. The authors point out that the implementation of broken windows policing strategies should not only focus on reducing disorder, but also on preventing the citizen's fear of crime (Skogan 1990; van der Weele et al. 2017; Weisburd et al. 2010).

Braga et al. (2015) analyzed different disorder policing programs by implementing several experiments. Broken windows policing is basically based on zero tolerance policing, where the

police applies strict law enforcement. However, studies show that this strict law enforcement type is not always effective. Problem-oriented policing strategies make citizens actively involved in problem-solving interventions. These strategies are more effective in order to reduce urban blight and lead to higher crime rate reductions than strategies that only target untended behavior (Braga et al. 2015; Skogan 2008).

As discussed in this section, there is discrepancy about the evidence of the Broken Windows Theory and the different disorder policing strategies. In general, it can be noted that there is a relationship between crime and urban blight, whereby the scope and the correlating factors of urban blight and crime are not always obvious and equal.

2.2 Geospatial technologies

Geospatial technologies are frequently used methods for spatial data storage, acquisition, analysis, modeling, and visualization. These technologies include Global Navigation Satellite Systems (GNSS), Geographic Information Systems (GIS), remote sensing, photogrammetry, laser scanning, conventional survey methods, etc. Although these methods are advanced and can be used in a broad variety of location-based services, some limitations can also be found. For instance, satellites cannot efficiently capture vertical surfaces due to its perspective. Unmanned Aerial Vehicles (UAV) have the right perspective to capture vertical surfaces and images provide a high resolution, however, this method is limited due to legal issues. Depending on the local legislation, UAVs are not allowed to fly in urban areas unless permission is granted. Conventional survey techniques, such as handheld GPS devices for precise positioning of contextual data, are time-consuming and therefore not sufficient to study large areas (Strelnikova et al. 2018). Moreover, Google Street View has been used to observe the environment. Although this methodology is efficient and cost-effective, the temporal stability of pictures is not provided and therefore not applicable to spatio-temporal studies (Curtis et al. 2013c).

Currently, it is of interest to find time-efficient and cost-effective methods without these limitations, that can collect contextual characteristics and can be applied to identify spatial correlations within a GIS (Curtis et al. 2015).

2.2.1 Spatial video technology

Spatial video, also known as videography or Spatial Video Acquisition System (SVAS), is a newly developed powerful technology that allows a collection of contextual field data for a fine-scale research. This technology can be applied in a wide range of disciplines, particularly in a geographic context. By applying the spatial video approach, spatio-temporal data can be collected in order to analyze geographic phenomena and environmental changes. Spatial video is considered as a ground level remote sensing technology and enables the improvement of environmental monitoring by combining Global Positioning System (GPS) and video. GPS sensors are linked to the spatial video, so that each recorded frame contains information about its geographical location and has a timestamp. The spatial video cameras can be mounted onto different surveying vehicles, such as cars, motorbikes, bicycles, or boats. Depending on the number of cameras, the recording of multiple angles is possible (Curtis et al. 2013b; Curtis et al. 2015).

In recent research, this novel spatial video technology has been used in several studies. Examples are the analysis of seasonal changes of cholera in endemic areas and the identification of health risks, like tuberculosis, by understanding the neighborhood context, where contextual characteristics like trash accumulation, standing water, presence of dogs or human activity is extracted from video recordings. These data are analyzed to find spatial patterns and to enrich spatial epidemiological analysis (Curtis et al. 2016; Curtis et al. 2015). Next to health issues, spatial video is also applicable to post-disaster analysis to conduct spatio-temporal research in order to document neighborhood recovery processes after a firestorm or hurricane (Mills et al. 2010). Furthermore, an underwater spatial video has been developed, where the GPS and cameras are attached to the boat to analyze the health status of coral (Riegl et al. 2001). Moreover, spatial video has been used in crime-related studies to collect contextual data (Curtis et al. 2013a).

2.2.2 Geo-narrative technology

Spatial video technology can be extended with geo-narratives. In addition to the spatial component, audio data is collected in the form of interviews or commentary to examine people's perceptions at specific locations. The environment is used to stimulate the discussion in order to get a better understanding about the occurrence and context of phenomena. The audio recordings of this narrative are linked to the location of the video with a time stamp. The understanding of contextual

characteristics can be extended through this mixed-methods approach (Mills et al. 2010; Curtis et al. 2015). Since qualitative methodologies are widely used for human-geographic research, a geo-narrative is an advanced and easy-to-use tool in qualitative research. Kwan and Ding (2008) define a geo-narrative as a GIS-based narrative analysis. Narrative analysis focusses on the experience of people through stories based on the social and environmental context, so perceptions based on their knowledge and personal experience can be captured (Curtis et al. 2015).

The geo-narrative is a novel technology, therefore not many studies have yet been conducted. An example where geo-narratives have been utilized is in post-disaster recovery and health studies, like mosquito control. The knowledge and experience of health experts can be captured to add an insight contextual resource to the visual component of spatial video (Curtis et al. 2015).

2.3 Methods to measure urban blight

Previously, researchers have used the Systematic Social Observation (SSO) method or self-report measures to assess disordered public spaces. Sampson and Raudenbush (1999) utilized the SSO method by applying analogue videos, where permanent visual records are collected while driving. Physical disorder indicators (e.g. garbage, graffiti, abandoned cars, etc.) and social disorder indicators (e.g. loitering, public consumption of alcohol, presumed drug sales, etc.) were extracted from video recordings. Although urban environments can be recorded with the analogue video and disorder indicators can be identified, the data cannot be integrated into a GIS, since images are not linked to coordinates. Therefore, the spatial video technology is a significant development for spatial analysis, since spatial and temporal data are available due to the integration of GPS sensors, which makes the visualization of data into a GIS possible (Mills et al. 2010; Curtis et al. 2013a).

As for self-report measures is concerned, the residents provide information about their own neighborhoods. This methodology includes the collection of subjective data, such as fear of crime and the perception of safety in public places (Marco et al. 2017). The “Ross-Mirowksy neighborhood disorder scale” is an index that has been utilized to collect these subjective measures. The index contains measures of physical disorder indicators and social disorder indicators. A reliable sample of inhabitants is asked to assess pre-defined statements about the perception of disorder in their neighborhood based on the different disorder indicators. Subjective measures are

compared with objective measures, which include data from census tracts, such as crime rates, population density, poverty, etc. (Ross and Mirowsky 2001). However, the self-report measure methodology is time-consuming and can be dangerous for research staff, since they have to stay physically in the high crime neighborhoods and to speak to people they do not know.

2.3.1 State-of-the-art methods

Google Street View (GSV) has been used in recent studies as an alternative to the social observation method. Utilizing GSV, the systematic observation can be conducted remotely. This method is beneficial, because it is cost-effective and safe, and research can be expanded to larger areas where physical presence is not necessary. GSV is freely available and includes high-resolution 360° images of many areas in the world. Limitations of GSV are the flexibility and stability in the temporal component of images (Curtis et al. 2013c; Marco et al. 2017).

Spatial video and geo-narrative technology can be used as new powerful tools to assess and evaluate objective and subjective measures of disorder. The utilization of spatial video has considerable advantages over other methods. It enables a time-efficient, cost-effective, and easy-to-use data acquisition method that collects contextual data assigned with necessary attributes. The required time for fieldwork can be reduced and the processed data can be easily used for spatial analysis within a GIS. Unlike Google Street View, the collection of spatial video data is under control of the researcher and therefore more flexible to use. The geo-narrative method enriches traditional spatial quantitative approaches with qualitative data. Geo-narratives are a good opportunity to involve people or communities in regard to a specific problem, and to identify important factors to find spatial and temporal correlations (Curtis et al. 2015).

Since the aim of this research is to identify urban blight factors and to integrate social factors, spatial video and geo-narrative will be tested and evaluated as a new technology to study crime-related factors. The collected urban blight indicators, crime rates, and subjective crime data will be overlaid to find correlations and patterns between these three parameters.

2.3.2 Urban blight studies in Baton Rouge

Baton Rouge City Parish officials have been conducting studies to analyze the relationship between crime and distressed properties in East Baton Rouge Parish. In the final crime report of the year

2017 (Moore 2018) it is stated that a significant correlation between crime and blight could be identified in Baton Rouge. Based on this crime report, the Baton Rouge's Mayor-President Sharon Weston Broome announced that it is of interest to find strategies to improve blight in Baton Rouge:

> "The Blight Strike Team brings together several community partners with an interest in swiftly and efficiently addressing blighted properties throughout East Baton Rouge Parish […] I look forward to working with them toward solutions. Blight elimination is of vital importance to improving public safety and advancing economic development efforts in our communities." (February 15, 2018) [1]

Since a relationship between crime rates and urban blight could be established, it is of interest to investigate the correlation of crime and urban blight in Baton Rouge in more detail. A recent study published in December 2018 by LSU researchers and the East Baton Rouge District Attorney's Office (Valasik et al. 2018) examined indicators that led to high crime rates in specific neighborhoods in Baton Rouge. The blight data utilized in this study came from the Baton Rouge Open Data Portal. The data set included reported instances of blight by citizens through calling the City Parish service number 311 or through submitting an entry online using the Red Stick 311 mobile application. The results of the study showed that there was a strong relationship between homicides and urban blight, and that homicides are more likely to occur in proximity to convenience stores. The researchers developed a model that can predict where homicides are most likely to occur in the future, based on the concentration of blighted properties and the presence of convenience stores.

The identification of urban blight can be improved utilizing the spatial video and geo-narrative technology implemented in this study additionally to the 311 reported data. This can be an additional geoinformation technology for the Baton Rouge City Parish officials and local law enforcement agencies for identifying urban blight and crime-related factors to reduce crime rates in Baton Rouge.

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[1] https://www.brla.gov/CivicAlerts.aspx?AID=62

Chapter 3

3 Conceptual Framework

Crime types and physical urban blight indicators are the main variables within the scope of this research. This paragraph discusses crime types and physical urban blight indicators that are relevant to study urban neighborhoods. The derived indicators are presented in criteria catalogues in Sections 3.1 and 3.2 to guarantee the consistency of classification, followed by an entity-relationship diagram, and a workflow diagram.

3.1 Criteria catalogue crime types

It is important to distinguish between different crime types, since the spatial distribution of criminal activities depends on its type (Wilson 2005, pp. 67–68). Crime types that are important for this research are based on crime types reported by the Baton Rouge Police Department (Moore 2018; Open Data BR 2019).

Table 1 illustrates the relevant crime types, which include assault, battery, burglary, criminal damage to properties, firearm, homicide, narcotics, nuisance, robberies, and theft.

Crime type	Description	Source
Assault	Person making a physical attack on another person.	(Moore 2018; Anliu Jiang 2017)
Battery	Criminal offence involving the unlawful physical acting upon a threat.	
Burglary	Unlawful entry into a building for committing an offense.	
Criminal damage to property	Damage or destruction of public or private property, caused either by a person who is not its owner or by natural phenomena.	
Firearm	Violence committed with the use of a firearm (gun or small arm).	
Homicide	One human killing another human.	
Narcotics	Synthesized from opium for medicinal use.	

Nuisance	Class of common law offences in which injury, loss or damage is suffered by the local community as a whole rather than by individual victims.	
Robbery	Taking anything of value by force, or by putting the victim in fear.	
Theft	Action or crime of stealing.	
Vice	Immoral, criminal behavior; offend morals of community e.g. prostitution.	
Other	e.g. car violation, extortions, fugitives, stalking, etc.	

Table 1. Crime type classification

In order to avoid low counts of crime incidents, vehicle burglaries, residential burglaries, and nonresidential burglaries have been classified into one group “burglary”. The crime type “robbery” includes individual robberies and business robberies. In order to protect the privacy of sexual assault victimizations of juvenile victims, these crime types will not be included in the research (Moore 2018; Anliu Jiang 2017; Open Data BR 2019).

3.2 Criteria catalogue urban blight

Up to now, no standardized measure or index of blight indicators exist to operationalize urban blight. The criteria catalogue illustrated in

Table 2 shows the main variables that are relevant for studying urban blight in Baton Rouge, or similar cities. The indicators in the criteria catalogue are derived from variables that are mentioned in the literature review in Section 2.1 (Skogan 1990; Hinkle and Weisburd 2008; Maghelal et al. 2013; Weisburd et al. 2010; Gau and Pratt 2010; Ross and Mirowsky 2001). The variables can be modified depending on the composition of the study area.

The focus of this case study is to assess physical urban blight. Therefore, only physical urban blight indicators are contained in the criteria catalogue. Within the physical urban blight criteria catalogue a separation is made between indicators that lead to the destruction of buildings and indicators that lead to environmental or infrastructural decay.

Physical urban blight type	Description	Source
1. Properties		
Abandoned property	Properties that show signs of decay or abandonment (e.g. doors are boarded up); Nobody lives in the house.	(Weisburd et al. 2010; Longley et al. 2015; Maghelal et al. 2013)
Broken window/door	Broken windows/doors are left unrepaired.	(Weisburd et al. 2010; Kelling and Wilson 1982; Pasadena community development commission 2010)
Boarded/covered window/door	Windows are boarded up with plywood or other material or covered with plastic, foil, etc.	
No glass in window/door	Windows/doors without glass and are left unrepaired.	
Building graffiti	Graffiti on buildings. *Note: Graffiti that is not situated on buildings is considered as infrastructural graffiti in environmental/infrastructural blight.*	(Weisburd et al. 2010)
Structural integrity	Severe cracks in the foundation of the building's structure; holes in plaster, wood, masonry, rooftop; unstable foundations.	(Pasadena community development commission 2010)
Building overgrowth	Unsafe amount of vegetation touching the building; constitutes fire, health, or safety hazard. *Note: overgrown vegetation that does not touch a building is considered as overgrown vegetation in environmental/infrastructural blight.*	(Pasadena community development commission 2010)
Other (specify)		
2. Environment/Infrastructure		
Damaged sidewalk	Structural failure in pavement what is left unrepaired.	(Gau and Pratt 2010; Ross and Mirowsky 2001)
Damaged roads	Structural failure in a road surface (e.g. potholes in asphalt pavement).	(Maghelal et al. 2013)

Overgrown vegetation	Any vegetation that appears to be overgrown in garden/vacant lots etc.; May block sidewalks. *Note: in contrast to building overgrowth, this indicator does not appear on buildings, but exclusively in empty spaces or on infrastructure.*	(Maghelal et al. 2013)
Litter	Single pieces of trash that are not within a garbage disposal bag; trash left on the ground in a public place.	(Weisburd et al. 2010)
Illegal dumping	Trash piles: unlawful deposit of any type of waste material (e.g. construction materials, tires, asbestos, etc.).	(Maghelal et al. 2013)
Unkempt areas	Empty areas (e.g. vacant lots) that appear unkempt (e.g. overgrown grass, trash, etc.).	(Maghelal et al. 2013)
Illegal parking	Car parked illegally on sidewalk; should be reported to city agency for removal.	(Weisburd et al. 2010)
Abandoned vehicle	Number plates missing, flat tires, missing wheels, broken windows, etc.; Any vehicle that has been parked illegally for >72 hours.	(Weisburd et al. 2010)
Infrastructural graffiti	Graffiti on walls or other surfaces. *Note: graffiti on buildings is considered as building graffiti in property blight.*	(Weisburd et al. 2010)
Other (specify)		

Table 2. Criteria catalogue for physical urban blight indicators

3.3 Entity-Relationship diagram

An entity relationship diagram (ERD) is used to describe data relationships and to design a database to serve the research purpose. The ERD is structured using entities that consist of different attributes and relationships between these entities (Longley et al. 2015). The diagram designed for this study consists of six entities, which are census block group, building, environment/infrastructure, physical urban blight indicator, criminal event, and inhabitant.

The aim of this research is to standardize physical urban blight on a census block group level in order to compare the analysis results between different census block groups. A census block group consists of buildings and environmental/infrastructural features. Building types for example include residential properties and commercial properties. Environmental feature types include for example vacant land, sidewalks, streets, garden/park, recreation areas, etc. The attribute "urban blight category" in the entity "census block group" determines the final level of urban blight depending on the number and intensity of physical urban blight within a census block group.

Additionally, aggregated measures about inhabitants, such as the mean annual household income, age, unemployment rate, etc. are connected to the corresponding census block group in order to include objective/quantitative data. The last feature that is influences the life quality of a census block group is "criminal event". This entity includes the crime type (described in the criteria catalogue in Section 3.1) and is important to answer the research question: *What kind of relationship exists between physical urban blight and crime in Baton Rouge?*

Figure 2 illustrates the proposed entity-relationship diagram including the entities, their attributes, and their relations.

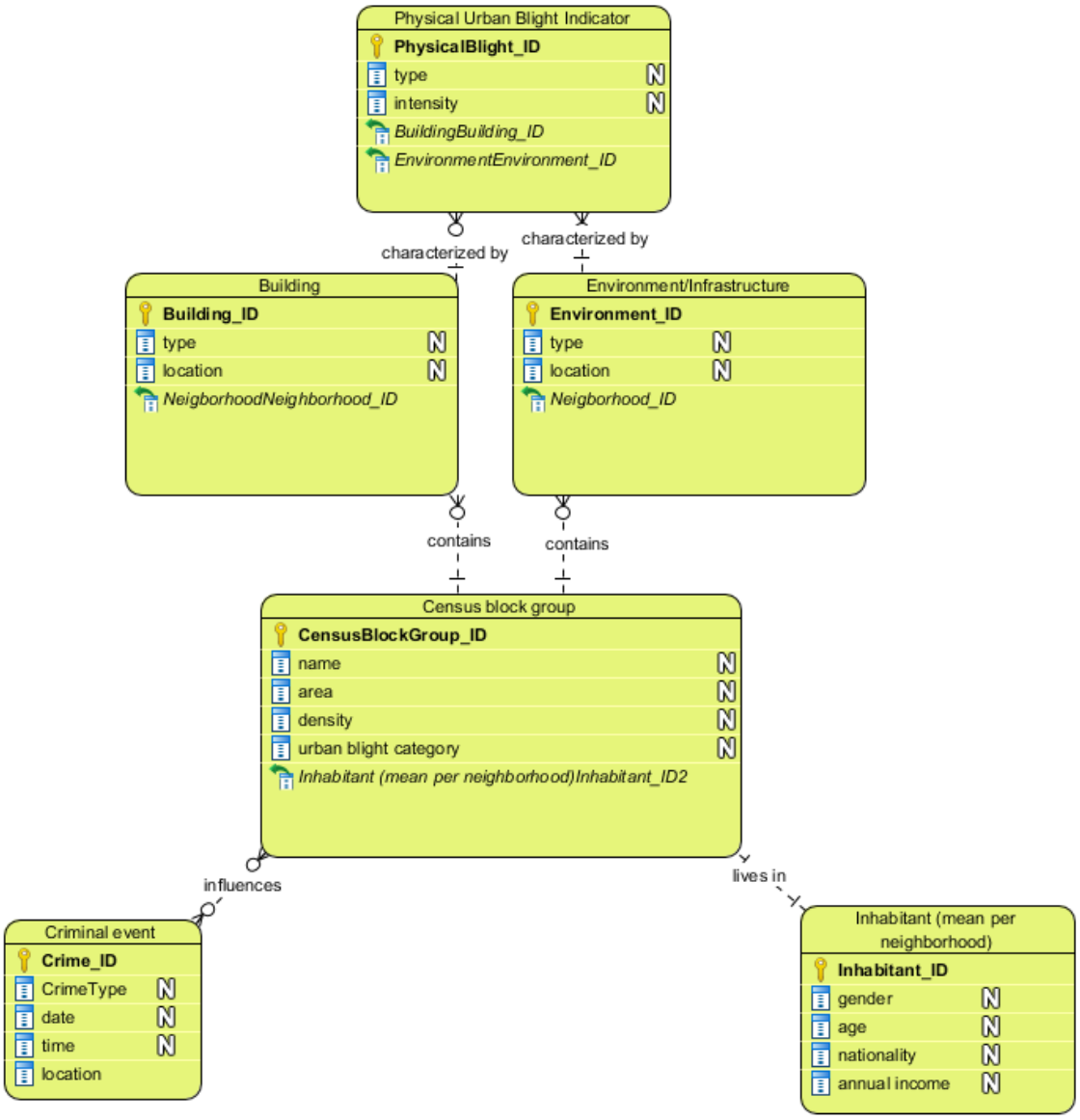


Figure 2. Entity-relationship diagram for standardizing physical urban blight

3.4 Workflow

Figure 3 illustrates the workflow diagram for the methodological approach. The workflow is divided into data collection, data post-processing, data manipulation and analysis, and data visualization. These steps are described in more detail in Chapter 4.

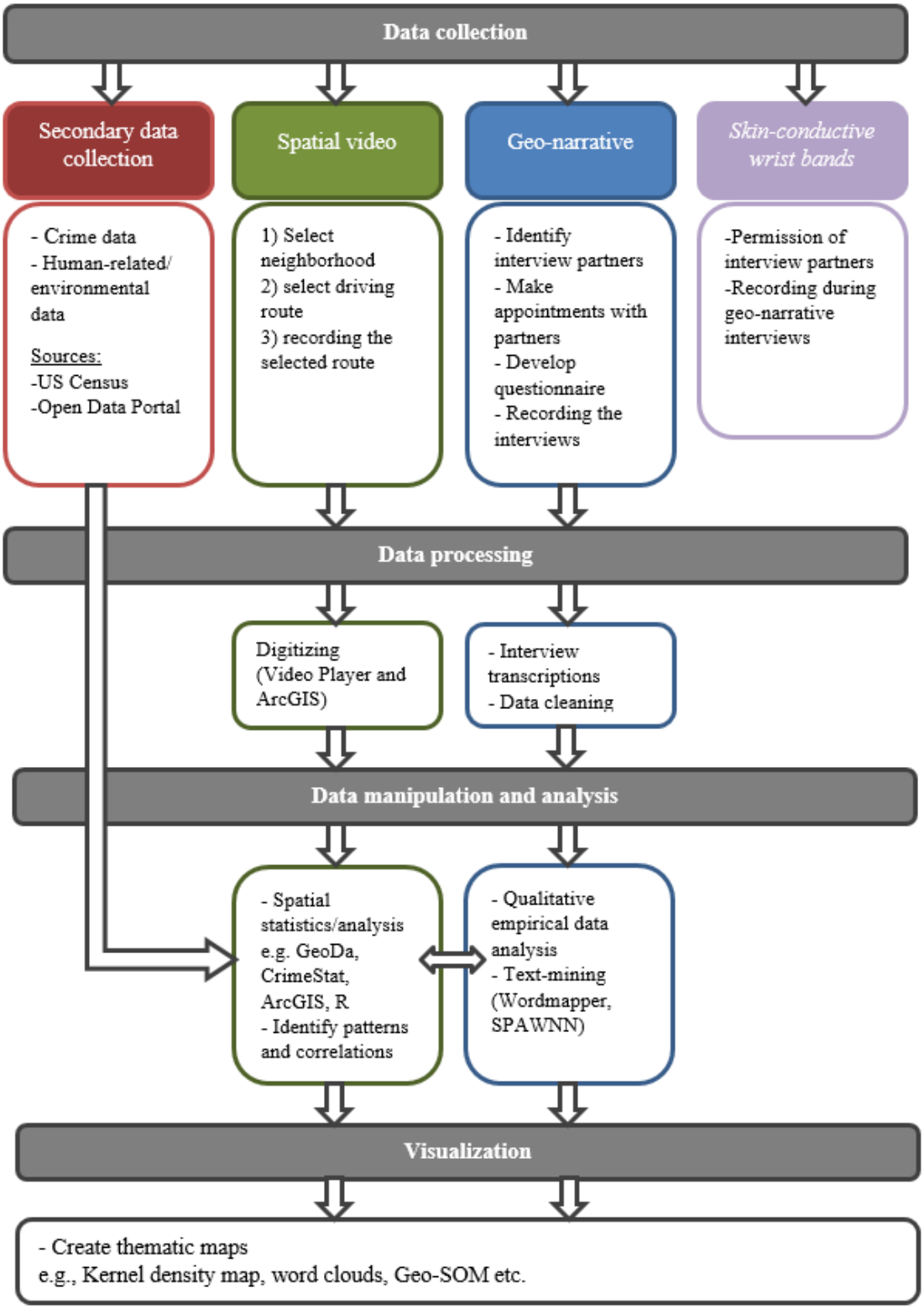


Figure 3. Workflow diagram

Chapter 4

4 Methodology used to collect, process, and analyze urban blight and perceived safety

This section describes the workflow steps for the methodological approach, including data collection, data processing, data analysis methodologies, and data visualization techniques in more detail.

4.1 Data collection methods

The methodology is organized twofold: In the first objective, crime and human-related data are gathered from institutional open data sources, such as the Baton Rouge Police Department, LSU Police Department, and US Census. These data are geocoded and cleaned for further analysis. Second, the fieldwork data acquisition utilizes spatial videos, geo-narratives, and skin conductive wristbands. All acquired data are subsequently fused into a GIS environment.

Participants are asked to fill in a questionnaire in order to collect background information about the participant's perceptions of safety/crime in Baton Rouge before the field data collection takes place. Additionally, participants are asked to mark places on the map where they feel unsafe.

The field data collection proceeds with a mixed-methods approach. As introduced in Sections 2.2.1 and 2.2.2, spatial video and geo-narratives are utilized to collect urban blight indicators and data about the perception of crime. Open Street Map information is used to define routes for the video acquisition in neighborhoods with a very high, high, medium, low, and very low density of crime.

The spatial video technology allows acquiring video data that include information about the geographical location of each recorded video frame. The urban blight variables defined in the criteria catalogue in Section 3.2 are identified to locate their presence in Baton Rouge. Five extreme

sport cameras from the brand Contour +2[2] are utilized to record the data while the vehicle is driving. Using suction window clamps, one camera is mounted on the inside windshield (Figure 4c). The other four are placed in the back of the car, two on the left and two on the right inside windows (Figure 4a, b). The data collection can be implemented by using only one camera on each side, however, one extra camera on each window is used to guarantee a backup in case one camera does not record properly. The placement of the cameras enables a wide viewshed for the digitization process in the next step. Since the data collection is partly implemented in environments with a high level of criminal activities the cameras are attached to the inside of the vehicle for unobtrusive data collection. The Contour +2 cameras are equipped with GPS sensors to collect accurate data about the location of the recorded video frames. Multiple cameras are used in case a video recording or GPS connection fails. Video recordings on high definition (1080p) mode are possible, which means that images are still clear, when the car drives at speed limit. In power mode, the battery lasts for approximately two hours, but can be extended while connecting to the car's charger (Figure 4d). A four-hour HD video recording can be saved on a 32 GB memory card. It will be saved in mp4 format with embedded GPS tracks (Curtis et al. 2013b; Curtis et al. 2015; Strelnikova et al. 2018; Mills et al. 2010).

[2] http://contour.com/

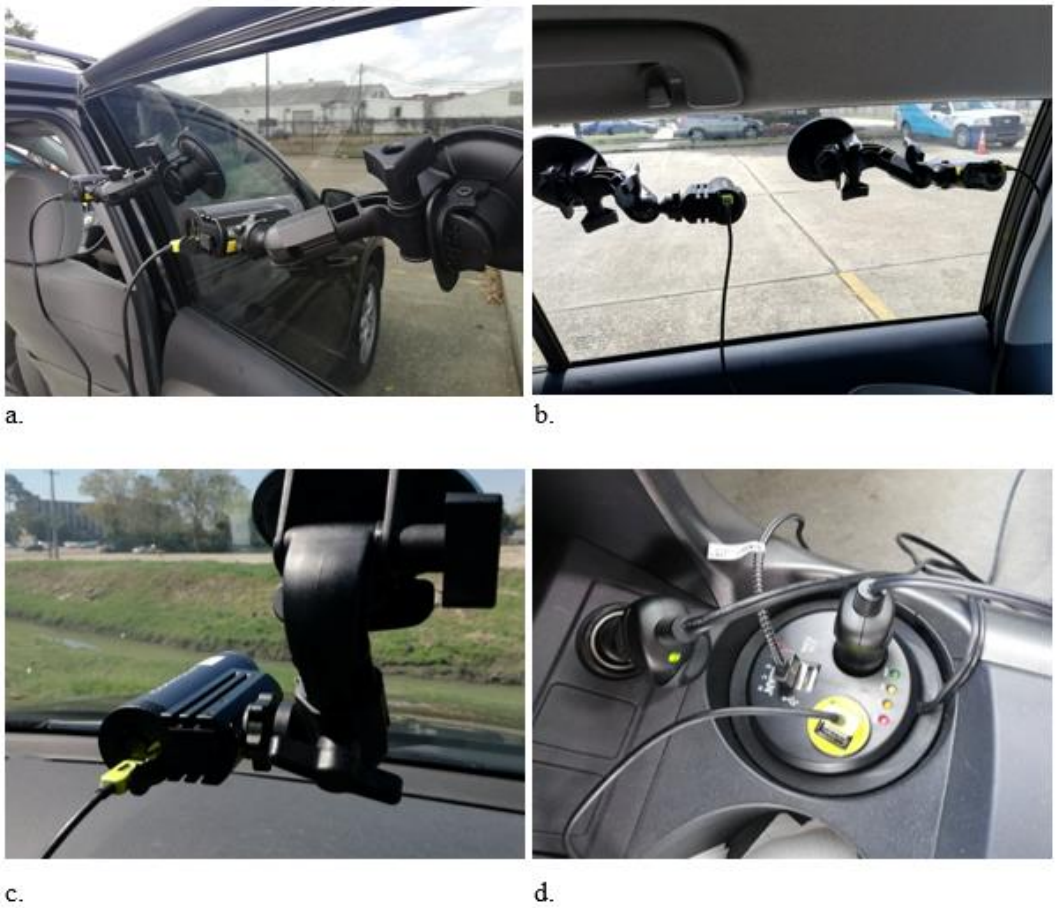


Figure 4. Installment of spatial video equipment; a) two cameras on right inside window, b) two cameras on left inside window, c) camera on inside windshield, d) charge equipment

Voice recordings are collected by applying the geo-narrative technology in addition to the spatial video. Geo-narratives are used to collect empirical data to get information about how individuals perceive crime in a specific neighborhood based on personal experiences. Through consistent tracking, unstructured interviews from various demographic groups, i.e. experts, local stakeholders, and students driving a pre-defined route are recorded, simultaneously to spatial video recordings to analyze narratives in space. The environment is used to stimulate the discussion with the corresponding participant, providing their knowledge and experiences. Participants are asked to talk about their perception of safety, fear of crime, indicators that influence their perceptions, and familiarity with the environment during drives. The Contour +2 cameras contain an internal microphone, however an external microphone or a phone recorder can be used to provide better quality recordings since there are many background noises in the car. Audio recordings are

connected with the GPS track of the cameras using time stamps. There is a need to have at least three people in the car, including a driver, an interviewer, and a participant of the empirical study (Curtis et al. 2015).

At the same time, the test subject is equipped with an E4 wristband from the company "Empatica"[3] (Figure 5). This skin conductive wristband is a wearable research device that is equipped with high quality sensors for measuring physiological parameters (i.e. blood volume pulse, skin temperature, heart rate etc.) to determine individual emotions and moments of stress. However, little research has been done on the additional benefit of physiological sensors for safety perception until today. The interpretation of the acquired physiological data requires the knowledge of medical experts. The data collection with the skin-conductive wristbands will be implemented in this study, however, further analysis will be done in cooperation with researchers working on the "Urban Emotions project" [4]. Experts from different research field work on this project and they developed an algorithm to extract moments of stress from the wristband sensors and they have experience how to interpret the physiological measurements based on urban context.

Figure 5. E4 Empatica skin-conductive wristband

4.2 Data processing

Crime incidents are based on address information. These addresses have to be assigned with x- and y- coordinates. Therefore, geocoding - turning an address of a crime incident into a point on a map

[3] https://www.empatica.com/research/e4/

[4] Resch et al. https://giscience.zgis.at/urban-emotions/

- is an important process in most types of crime analysis. Additionally, inaccurate records have to be detected and corrected or deleted from the geodatabase (Hart and Zandbergen 2012).

Furthermore, locations of every blight indicator have to be extracted from the recorded videos based on the pre-defined criteria catalogue in Section 3.2. Corresponding locations of physical urban blight are digitized in order to convert the collected information into a digital format. Before starting the digitization process, the recorded spatial video data is downloaded by extracting the data on a micro SD card to the computer. The size of the output file of the full HD 1040p mode from the Contour +2 video cameras is approximately 1 GB per 9 min. To view video recordings and the driven GPS track, a camera player software developed by Andrew Curtis et al.[5] is used. An example of the video player software is shown in Figure 6. After importing videos into the software, the video files can be viewed. The GPS track is shown in an embedded map (Figure 7), resembling the driven route on the earth surface. However, it should be taken into consideration that the track can deviate from its real location due to the quality of the GPS signal.

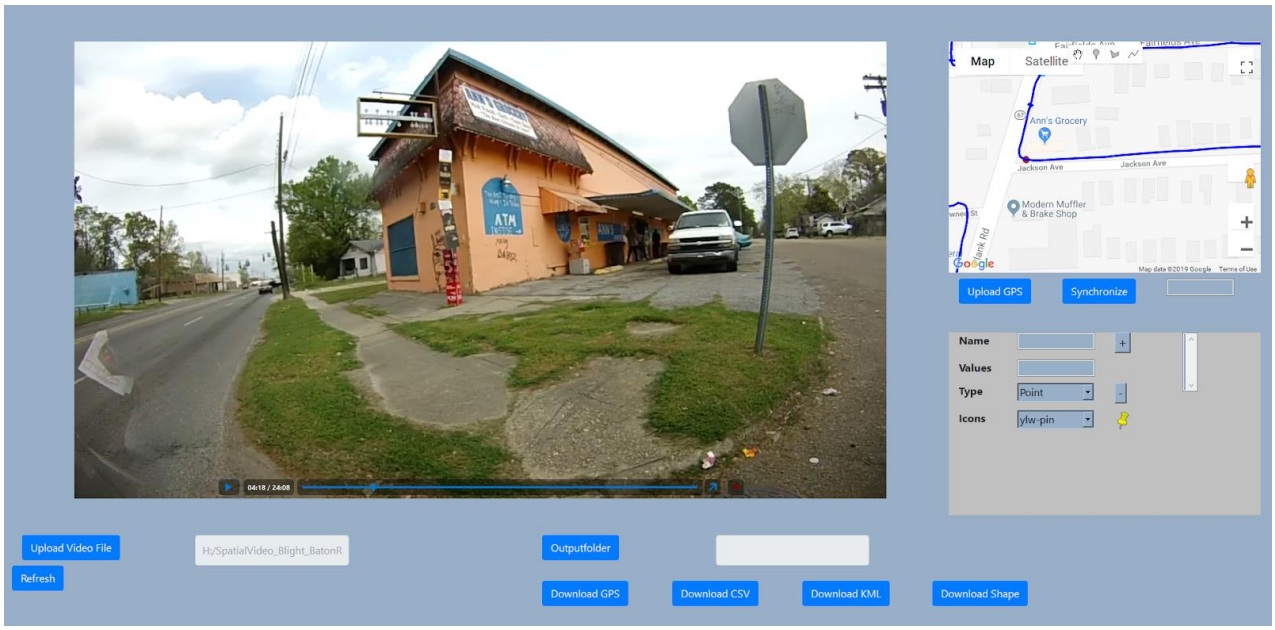


Figure 6. Example of video player with embedded GPS track

[5] https://www.kent.edu/geography/profile/andrew-curtis

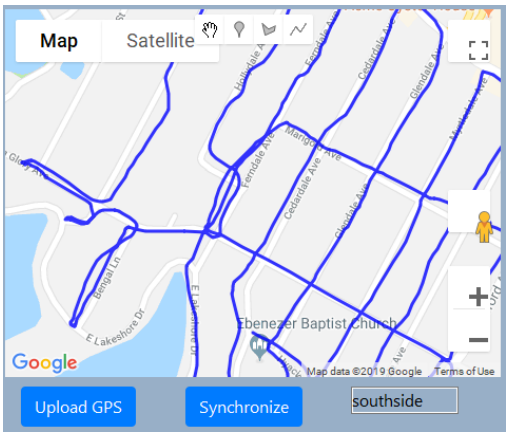


Figure 7. Example of GPS track of recording

The digitization of urban blight locations is implemented in ArcMap. When a blight indicator is identified on the video recording, a point symbol is placed in the center of the corresponding building or parcel on the map.

For the text analysis of the geo-narratives, the recordings have to be transcribed, using the time stamp for each sentence. The transcripts are then imported into the software "WordMapper", developed by Andrew Curtis et al.[6] (Figure 8), connecting the corresponding timestamp of the transcripts with the GPS track of the video. The sentences can be shown on the map by inputting keywords that should be contained in the sentence. It is possible to assign the sentences to specific defined categories.

[6] https://www.kent.edu/geography/profile/andrew-curtis

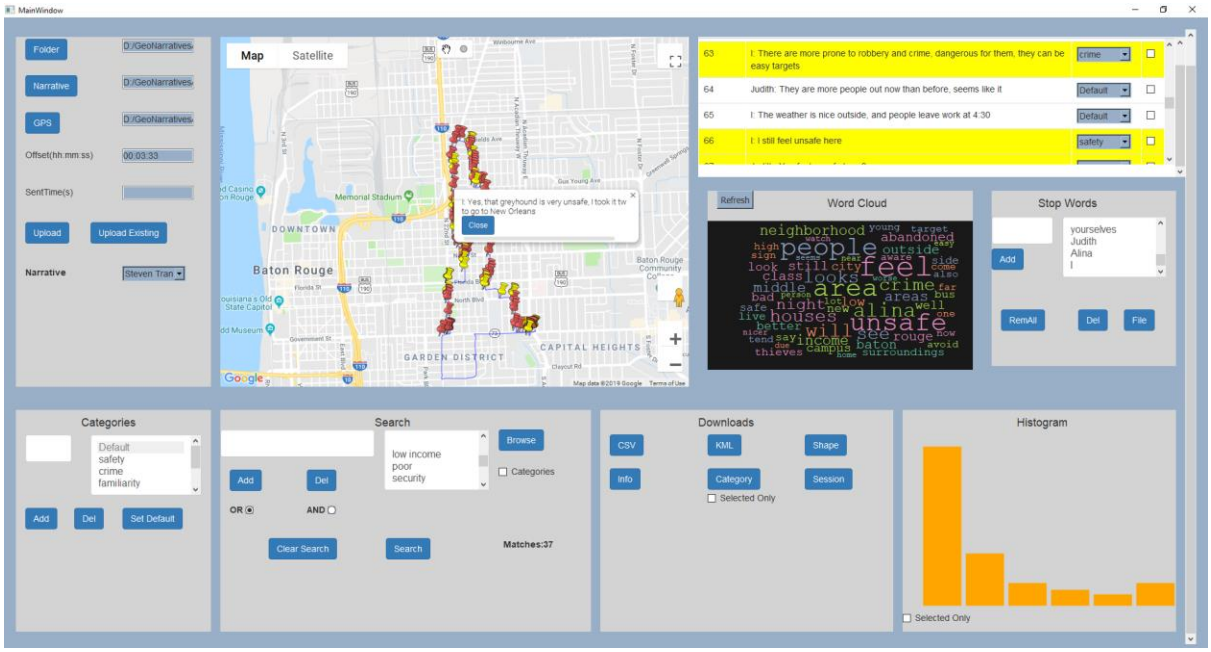


Figure 8. Example of WordMapper software

4.3 Analysis methodology and data visualization

The digitized urban blight data from the spatial video are analyzed by applying different spatial statistical methods. Subjective crime data captured with geo-narratives are analyzed using text-mining methods.

4.3.1 Spatial analysis

After completing the digitization process a series of spatial analysis methods are performed in CrimeStat 4.02 (Levine 2015), GeoDa 1.12 (Anselin 2019), ArcMap 10.6 (ArcMap 2018), and R. Different spatial statistical approaches are applied for (1) analyzing overall distributional patterns of the collected point data, (2) identifying the existence of spatial clusters, and (3) investigate correlations between physical urban blight indicators and crime types.

Descriptive statistical methods, including the median center of the blight points and standard deviational ellipses of different blight types, are used to identify the spatial distribution of urban blight and various crime types. The spatial median is the intersection of the median of the X-coordinates and the median of the Y-coordinates. It is a useful statistic, because it is robust to

outliers (Levine 2015). The level of spatial dispersion is represented using standard deviational ellipses (SDE). The amount of extra space is minimized by using an ellipse instead of a circle. Ellipses help to explain the degree and the orientation of the locations (Eck et al. 2005; Levine 2015).

Anselin's local Moran's I (Anselin 1995) is used as a spatial autocorrelation technique for measuring the degree to which blight points are related to each other and to identify local clusters and local outliers. The values for Moran's I range between -1 (perfect clustering of dissimilar values), 0 (randomness), and +1 (perfect clustering of similar values).

Another analysis method is the Kernel Density Estimation (KDE). Kernel density estimation is an interpolation technique to find density values of urban blight (weighted and unweighted) and crime locations within the study area. The density value for each raster cell is calculated. The more urban blight/crime locations are found inside one specific cell or within adjacent cells, the higher the density value of this cell is. KDE results depend on the selected parameters, such as the kernel function type, cell size, and kernel function's bandwidth (Eck et al. 2005; Smith and Bruce 2008).

Moreover, blight and crime data are aggregated to census block groups for identifying the density of blight and crime. Since the data are analyzed on the census block group level and the number of census block groups (the sample size) is less than 30, the Spearman's rank correlation coefficient is used as a non-parametric version of the Pearson correlation to find dependencies between different blight indicators and crime types. The Spearman's correlation coefficient varies between -1 and +1. -1 indicates a perfect negative correlation, 0 no correlation, and +1 a perfect positive correlation (Chen and Popovich 2006).

Results of the spatial analysis are visualized by creating maps in ArcGIS to get a better understanding of the spatial distribution and the relationship between physical urban blight and crime. By visualizing the results in maps, it is easier to identify clusters and hotspots of blight and crime. The intensity of urban blight indicators can be standardized utilizing a classification scheme depending on their severity within an area. Urban blight is standardized into five categories from high to low, where category [level number 5] characterizes a critical high level of blight, [level number 4] shows a high blight level, [level number 3] a moderate blight level, [level number 2] indicates a low blight level, and the category [level number 1] indicates very low blight. Final

results are displayed in density maps aggregated at the census group block level and kernel density maps, where each census block group/grid cell is color-coded based on its density (Curtis et al. 2013b; Smith and Bruce 2008).

4.3.2 Text analysis

Qualitative data analysis (Mayring 2010) is carried out to analyze various points of view and subjective experiences of different participants of the geo-narrative survey. All data are anonymized to protect individual privacy. By connecting the GPS track of the driven route with transcripts of interviews, specific sentences or words can be shown as points in the map. Only sentences that belong to one of the five pre-defined categories (safety, crime, familiarity, blight/condition, wealth/status) are of interest for this research. By analyzing each sentence at the specific location, a positive, neutral, or negative feeling can be assigned with this text. Text-mining is the process of exploring unstructured text data. Various text-mining techniques are applied to analyze and cluster the frequency of specific words or the association of keywords to other words in order to implement structured data analysis and to interpret interview statements (Ananyan 2004). For analyzing word frequencies in a meaningful way, stop words have to be defined, which will not be considered in the analysis.

Text mining visualization tools, such as word clouds and histograms, can be created in the WordMapper software. Key terms relevant to the research topic are selected in order to construct word clouds. Words that occur more often appear bigger and more prominent than words that were mentioned less frequently. Moreover, interesting sentences of selected test subjects are visualized in ArcMap as points representing negative, neutral, and positive feelings

Additionally, self-organizing neural networks are applied as a new geo-visualization technique for revealing spatial clusters and patterns. A set of artificial neural networks (ANNs) are trained in an unsupervised manner to detect similarities in the input data. During the training, the neuron with the smallest distance (most similar) to the input vector is identified and referred to as the best matching unit (BMU). The number of clusters can be defined and visualized in self-organizing maps (SOMs). However, this technique does not include the spatial dimension. Bação et al. (2005) developed an algorithm to also include space into a SOM, the so-called Geo-SOM. This new SOM architecture integrates features of artificial intelligence-based clustering with GIS. The algorithm

is based on Tobler's First Law of Geography, that states that everything is related to everything else, but near things are more related than distance things (Tobler 1970). In Geo-SOM, the search for the best matching unit includes two phases. In the first phase the BMU is searched only comparing geographical coordinates of the input vector. Neurons that are similar in space are clustered. This output is used in the second phase to find similar attribute values to define the final BMU. In this research the combination between the categories (1) safety, (2) crime, (3) familiarity, (4) blight/condition, (5) wealth/status, and the assigned test subject's feelings: (1) positive, (2) neutral, (3) negative, are clustered. Depending on the BMU of the value combinations, clusters with maximum similarity values are identified applying the k-means clustering algorithm. K-means clustering determines the centroid of each cluster (i.e. cluster mean), which corresponds to the mean of the point that is assigned to the cluster. The number of clusters (k) has to be defined before starting the unsupervised machine learning algorithm. In the training process the algorithm selects randomly k objects from the data input. These selected neurons are the centroid of each cluster. In the next step the remaining neurons are assigned to its closest centroid using the Euclidean distance between the neuron and the cluster centroid. The open-source software SPAWNN[7] is used for spatial text analysis with self-organizing neural networks (Hagenauer and Helbich 2016).

[7] Spatial Analysis With Self-Organizing Neural Networks http://www.spawnn.org

Chapter 5

5 Implementation

This Chapter provides information about the geography and demography of the study area and the identification and selection of test units and test subjects for data acquisition. Moreover, the employed data sources followed by the data set preparation are described.

5.1 Study area

The research is implemented in Baton Rouge, the capital city of Louisiana (United States) located in the East Baton Rouge Parish (EBRP). The EBRP consists of four cities: Baker, Central, Zachary, and the City of Baton Rouge, illustrated in Figure 9 (EBRGIS Open Data 2019).

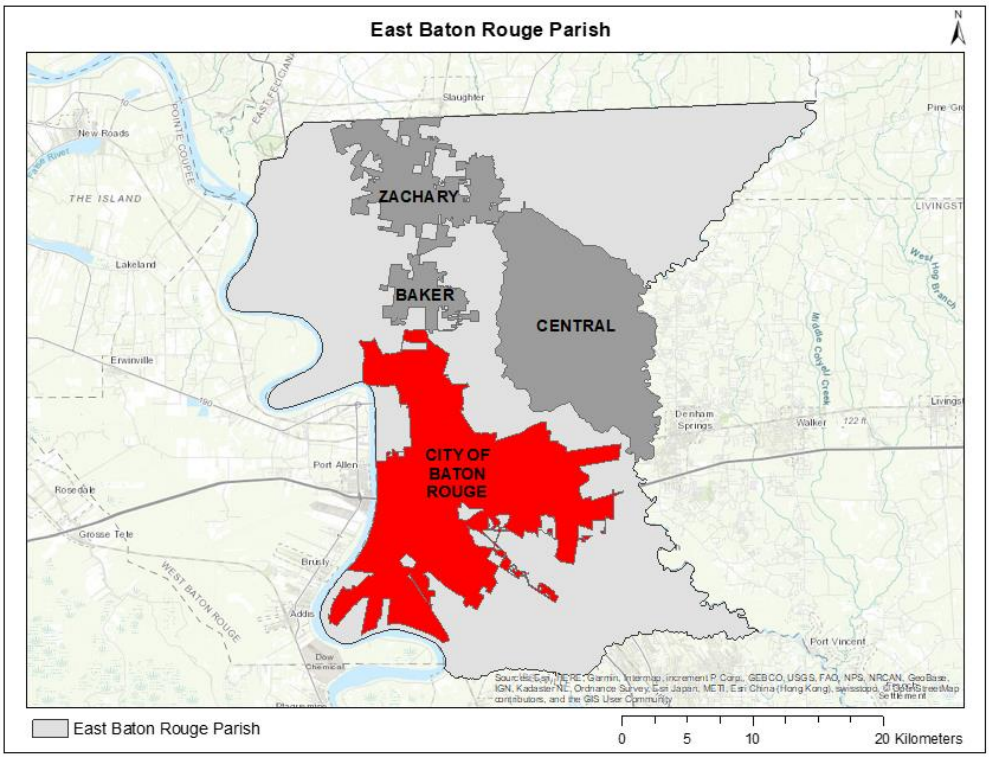


Figure 9. Geographic boundaries of East Baton Rouge Parish and cities inside the Parish

The area marked in red is the City of Baton Rouge and the focus of this study. The City of Baton Rouge consists of 58 neighborhoods and occupies an area of 123.84 square kilometer, located on the east bank of the Mississippi River. In the city of Baton Rouge live officially 229,422 inhabitants according to the most recent census from 2010, and an estimate of 221,599 inhabitants in July 2018, according to the US Census data. The ethnical diversity of Baton Rouge is illustrated in Figure 10, with the majority of residents being African American (54.8%), while white residents make up about 36.6% of the population (United States Census Bureau 2018b).

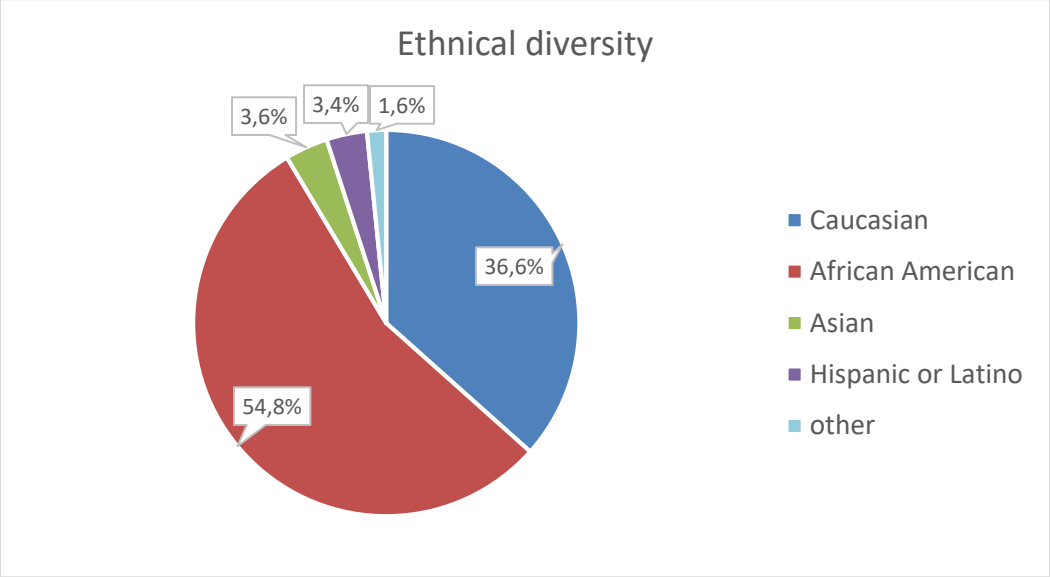


Figure 10. Ethnical diversity in the city of Baton Rouge based on the 2010 US Census

32.4% of persons who are 25 years or older have a Bachelor's degree or higher. The median annual household income, estimated in the period 2013-2017, was $ 40,948 and significantly lower than the national U.S. median household income of $ 60,336 (United States Census Bureau 2018b; Open Data BR 2019; United States Census Bureau 2018a).

According to the FBI's Uniform Crime Reporting (UCR) program, Baton Rouge is ranked as one of the most violent and dangerous cities in the United States (Kaplan 2019). The UCR program reports nationwide crime data and compares and ranks crime data in different US cities or states. Especially homicide rates in the city of Baton Rouge are significantly higher than the average national homicide rate (Moore 2018; Valasik et al. 2018). Different local law enforcement agencies are working within the East Baton Rouge Parish, such as the East Baton Rouge Sheriff's Office,

Baton Rouge Police Department (BRPD), Zachary Police Department, Baker Police Department, and the Louisiana State University Police Department. The primary law enforcement agency responsible for the City of Baton Rouge is the BRPD.

Figure 11 shows a kernel density map of crime incidents in the City of Baton Rouge and their neighborhoods. Crime types include burglaries, robberies, theft, narcotics, vice, assault, nuisance, battery, firearm, homicides, criminal damage to property, sexual assaults, and juvenile. The red color shows very high crime areas, the blue color shows very low crime areas. It can be concluded that crimes are concentrated in hotspots in the middle and northern parts of the city. The very low crime areas are located in the southern part of the city. In the year 2018, thefts occurred most often with 24 %. In relation to all crime types, homicides occur relatively rarely with only 0.8 %. However, by looking at the absolute number of homicides with 376 incidents in 2018, the number is critically high.

It should be noted that some parts of the city (i.e. swamps) do not contain crime data and are shown with an appropriate symbology on the map. Moreover, it should be taken into consideration that neighborhoods of the East Baton Rouge Parish do not necessarily follow the boundary of the city of Baton Rouge. Some neighborhoods share areas with the East Baton Rouge Parish, but also with the city of Baton Rouge.

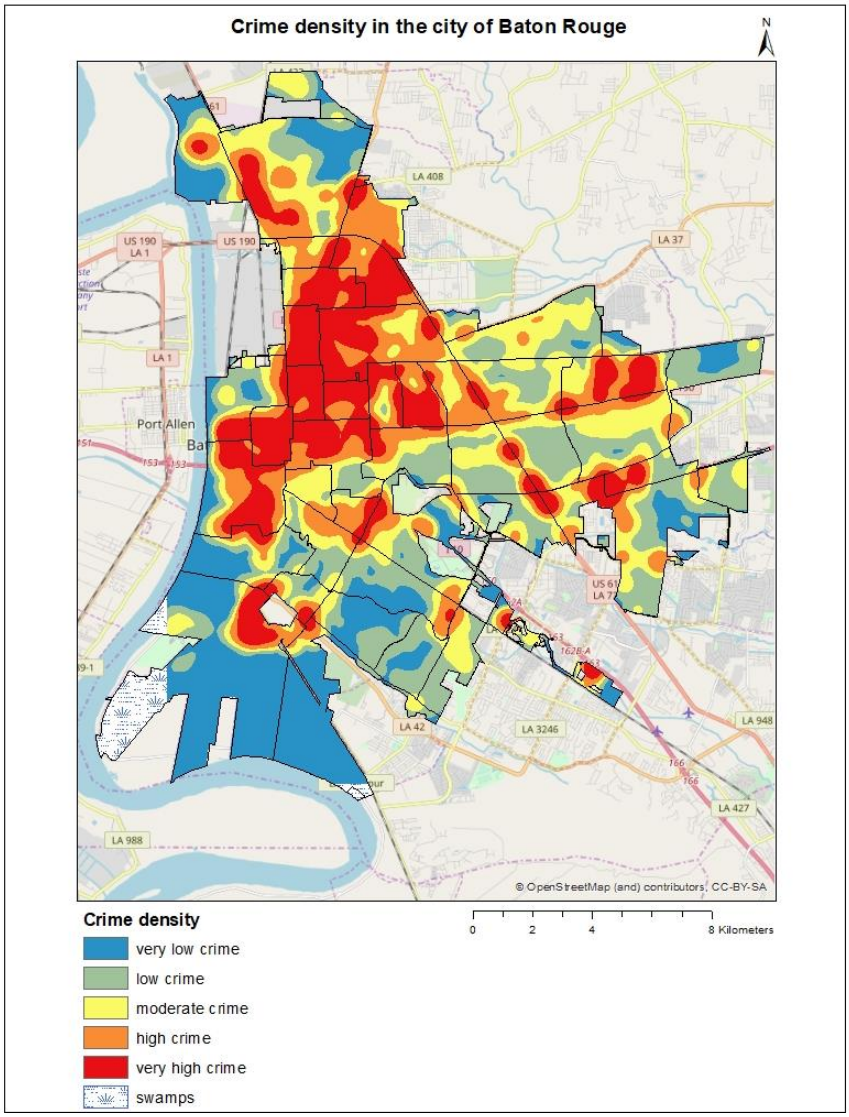


Figure 11. Crime density in the city of Baton Rouge in 2018

5.1.1 Units of analysis

5.1.1.1 Spatial unit

One essential step in geographic research is the selection of a coherent set of spatial units for data aggregation. A fundamental problem in geospatial research is the modifiable areal unit problem (MAUP) introduced by Openshaw (1984). The MAUP occurs because arbitrary boundaries such as administrative boundaries or cell grids are created in order to aggregate data. The results of any spatial statistical analysis always depend on the chosen spatial units. Therefore, it is important to

choose an adequate level of detail that best represents the research' purpose. No rule or standard for choosing the unit for data aggregation exists. Hip (2007) discusses the importance of selecting an appropriate spatial unit in crime and urban disorder studies. The author shows that urban blight and crime perception are localized phenomena. For example, one broken window or trash on the street may not characterize that the whole area is affected by physical disorder. Therefore, it makes more sense to choose a small spatial unit such as a census block or a census block group. Crime locations in Baton Rouge are not homogeneously distributed, therefore census block groups are chosen in order to identify variation in crime and urban blight within one neighborhood. Census block groups are divisions of a larger census tract. The East Baton Rouge Parish consists of 303 census block groups (United States Census Bureau 2011; EBRGIS Open Data 2019).

5.1.1.2 Site selection

Five neighborhoods within the city limits of Baton Rouge are selected for the spatial video data collection. Neighborhoods are chosen depending on the crime density, in other words the number of crimes divided by the neighborhood area in km². The crime density is divided into the following five classes using quantile classification: (1) very low crime, (2) low crime, (3) moderate crime, (4) high crime, (5) very high crime. The specific study area is chosen considering the following selection criteria: no highways, no big lakes, possible connectivity between individual areas chosen, many buildings, easy to navigate through by automobile, and possible similar street length. Moreover, a density map of the 311 reported urban blight data are examined to make sure that the study area includes blight areas.

Figure 12 shows a map with the neighborhood selection, where the red area represents the neighborhood with a very high crime rate (Fairfields), the orange area the neighborhood with a high crime rate (Mid City), the yellow is the neighborhood with moderate crime rate (Southside), the green neighborhood the area with a low crime rate (Pollard/Woodchase), and the area with the lowest crime rate is represented in the blue color (University Acres/Woodstone). In total, the five selected neighborhoods consist of 22 census block groups.

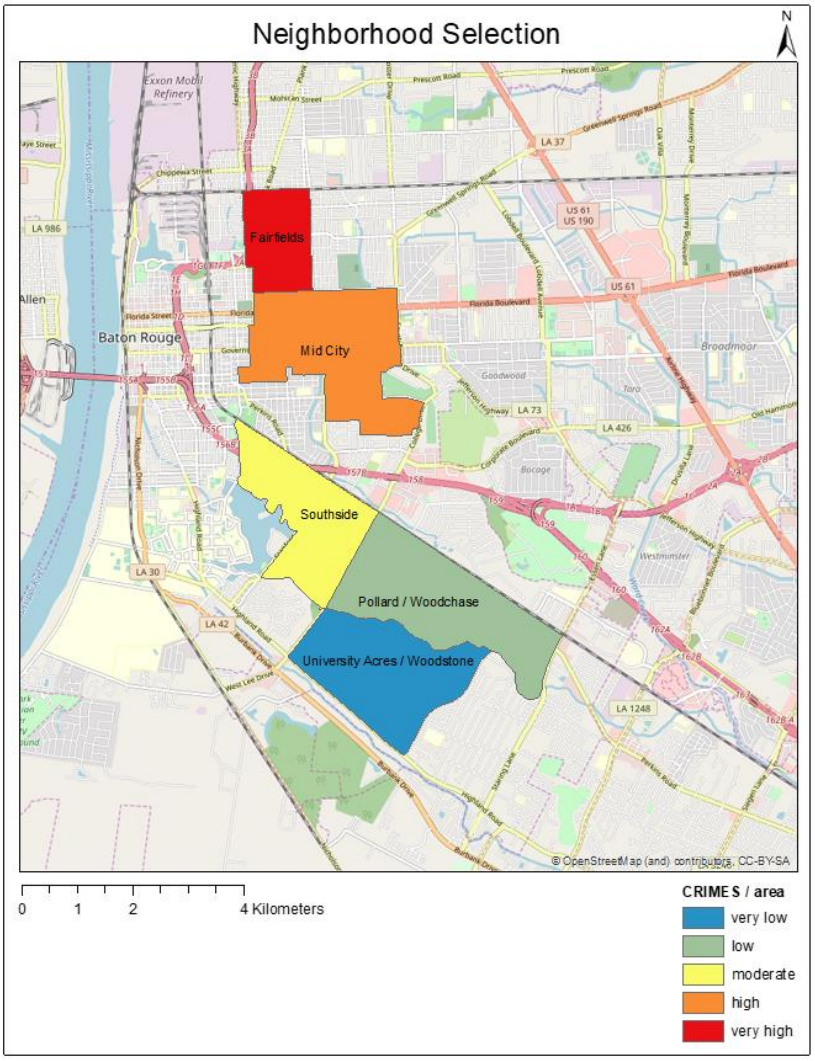


Figure 12. Neighborhood selection considering crime density

Before starting the spatial video data collection, an optimal route that covers all streets in the five selected neighborhoods has to be created. In order to cover all streets, some street segments have to be driven more than once. Also, one way streets have to be considered while creating routes. The application "Ride with GPS[8]" is used to plan the routes in advance and to navigate through the areas during data collection. The creation of routes is based on Open Street Map and Google Maps,

[8] https://ridewithgps.com/

since both maps show different information in some instances. Figure 13 shows an example of the route design covering all streets using the app “Ride with GPS”.

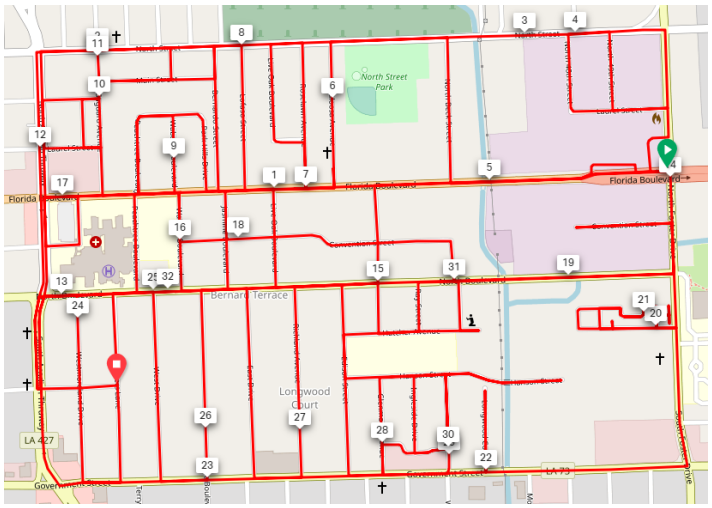


Figure 13. Example of a route design

Table 3 shows information about the population size, area, street network, number of buildings, crime counts, and crime rates per selected neighborhood. The street kilometers in all selected neighborhoods are similar, except in Mid City. The five selected neighborhoods are the most appropriate choice of neighborhoods considering all selection criteria.

	Population 2018	**Area [km²]**	**Street network [km]**	**Number of buildings**	**Crime counts 2018**	**Crime density [crimes/area] 2018**
Fairfields	4,239	2.16	50.57	2,110	1,305	604.17
Mid City	8,647	5.53	85.93	4,122	1,859	336.17
Southside	3,822	3.92	49.87	2,007	540	137.76
Pollard/Woodchase	3,916	5.64	47.95	1,520	539	95.57
University Acres/Woodstone	4,673	4.83	44.99	1,975	228	47.20

Table 3. Information about the five neighborhoods selected for this study

Based on the crime density in the five selected neighborhoods, one route for the geo-narrative field work is designed. This route is created addressing the following selection criteria: duration of 20-25 minutes; no high traffic density roads, while driving through low, medium, and high crime areas; and indicators of blight should be located on the selected route. Based on these criteria, the route presented in Figure 14 is chosen as an appropriate test route. The kernel density map in the background illustrates the density of crimes per grid cell with an individual size of 100 m² using a 5-class equal interval classification. The route passes through several high (red/orange) and low crime areas (green/blue) and is located within the Fairfields and Mid City neighborhoods.

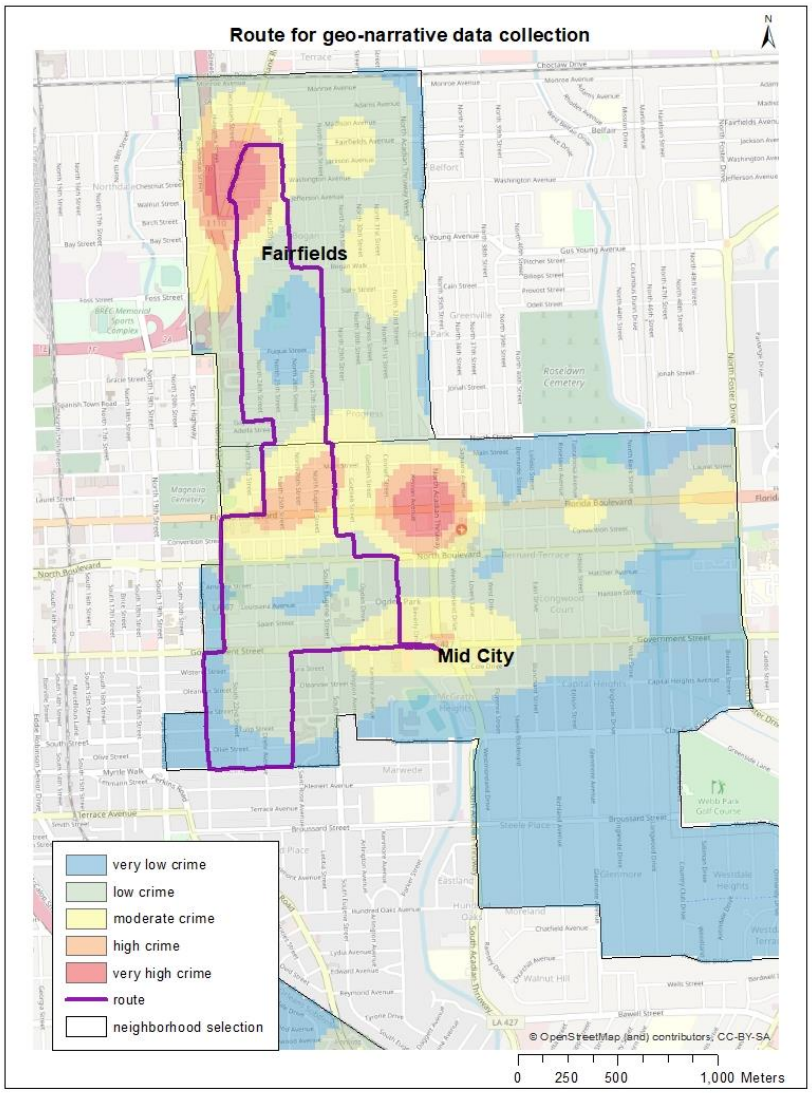


Figure 14. Selected route for geo-narratives field work

5.1.1.3 Test subjects

An appropriate sample size of test subjects is required for inference and validity of statistical results. Researchers suggest that there should be a minimum sample size of 30 and the sample should be randomly chosen (Hogg and Tanis 2010). However, it is not easy to meet the criteria in the limited time to undertake this study. To maximize the sample size, test subjects that best match the aim of the research are chosen.

In total 53 people participated in the safety assessment survey, which included (1) filling in a background questionnaire and (2) mapping areas in Baton Rouge where participants feel unsafe. 46 participants were students in Geography, Sociology or Social Work at LSU, 6 people represented non-student locals to Baton Rouge, and 3 people were non-student experts in the field of crime and/or blight. The age of participants that completed the questionnaire ranged from 19 to 72 and existed of 30 females and 23 males.

Similarly, for the geo-narrative study a group of students, non-student locals, and non-student experts were selected that greatly overlap with the cohort completing the safety assessment survey. In total 46 people participated in the geo-narrative study, where 32 people represented Geography/Anthropology and Sociology students, 9 people represented local stakeholders, and 5 people were experts in the research field. The age range of participants was between 19 and 95.

Test subjects had different nationalities and ethnical backgrounds (i.e. Caucasian, African-American, Hispanic, and Asian). The majority of participants held the US citizenship.

The geo-narrative results are mainly analyzed in a qualitative way.

5.2 Data sources

The data of this study include both primary and secondary data sources. Secondary data sources include crime data and socio-demographic census data. Primary data sources include (1) survey data based on questionnaires and on-screen mapping, and (2) field data collected with spatial video and geo-narratives. Figure 15 gives a graphical overview of the used data sources.

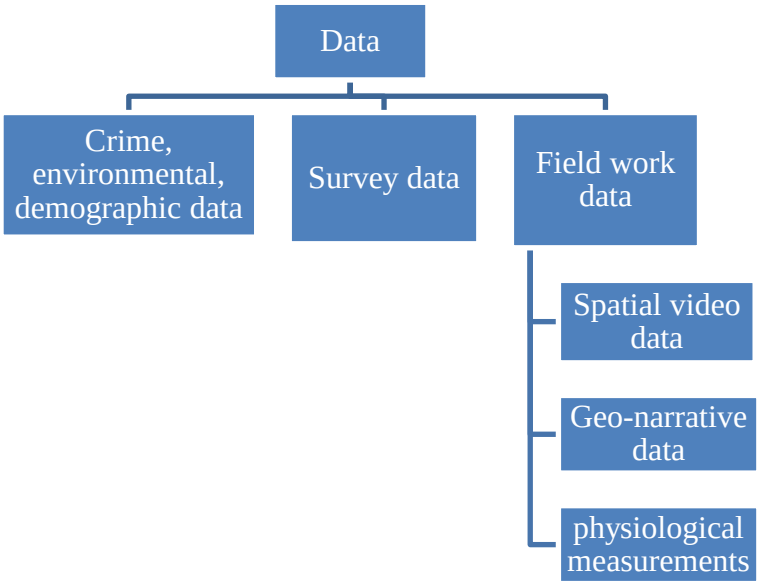


Figure 15. Data sources used in this research

5.2.1 Crime, environmental, and demographic data

Crime data are collected from official reports of the Baton Rouge Police Department and are available on the Baton Rouge Open Data Portal (United States Census Bureau 2018b; Open Data BR 2019; United States Census Bureau 2018a). All other secondary data for this research, such as boundaries, neighborhoods, and infrastructural data are obtained from the following governmental open data sources: (1) East Baton Rouge Parish GIS Open Data Map Portal[9], (2) Open Data Baton Rouge Portal[10], and (3) US Census (United States Census Bureau 2018b; Open Data BR 2019; United States Census Bureau 2018a).

5.2.1.1 Data set preparation

This research considers all crimes reported to the BRPD from January 1st, 2018 to December 31st, 2018. The data were downloaded on February 25th, 2019 using the Socrata API in R. The projected lambert conformal conic "NAD_1983_StatePlane_Louisiana_South_FIPS_1702_Feet" coordinate

[9] http://data-ebrgis.opendata.arcgis.com/

[10] https://data.brla.gov/

system is used in order to display the data set. The unit of projection is in U.S. survey feet, however, for the purpose of this study all measurements are converted into the metric system.

It should be noted that this crime data set does not include data obtained by the East Baton Rouge Sheriff's Office. Moreover, the BRPD does not follow the FBI's Uniform Crime Reporting (UCR) Program for reporting crime data. Crime types included in the BRPD data sets are described in more detail in the criteria catalogue in Section 3.1.

5.2.1.2 Data Quality

Data quality refers to the expectation that has to be met in order to fulfil their purpose in a particular context. The results of point data analysis in crime mapping relies heavily on the quality of geocoding, including (1) completeness, (2) positional accuracy, and (3) repeatability. Completeness is the percentage of addresses that can be geocoded and is commonly referred to as the match rate. The positional accuracy of data indicates how close each geocoded point is located to its actual location, i.e., its address. Repeatability refers to the sensibility of geocoding to variations in for example the input address, reference data, and geocoding software (Hart and Zandbergen 2012). Similar to completeness, the following errors can occur: misspelling of the street name, using abbreviations that are not recognized, using an incorrect street type, entering a location that is not known to the geocoding database, omitting to enter an address, etc.

There is no standard proportion of addresses that should be geocoded in relation to all addresses available. However, several criminal justice research attempted to establish a minimally acceptable geocoding match rate for crime data. Ratcliffe (2004) examined the effect of the percentage of geocoded records on the analysis results. Results determined that at least 85% of crime records should be geocoded in order to conduct a statistically reliable analysis. This value can be used as a minimum acceptable geocoding benchmark in spatial crime analysis.

Crime data for the East Baton Rouge Parish for 2018 contained originally 45,561 crime records, whereof 3,246 records had no x- and y-coordinates and thus needed to be geocoded using R. From this number 2,658 locations are successfully geocoded. However, the remaining 588 records do not have any address information and are thus not included in this study. Hence, 44,973 crime incidents could be geocoded. From this data set, a total of nine crime records are located outside of the Parish boundary or do not have an exact location and are removed from this research. This leaves a total

of 44,964 records to be located inside the EBRP. From this number the points within the City of Baton Rouge limits are extracted, with the final number of crime records for this analysis to be 44,554. Figure 16 illustrates the data set preparation/cleaning including the number of geocoded and other crime records selected for this study.

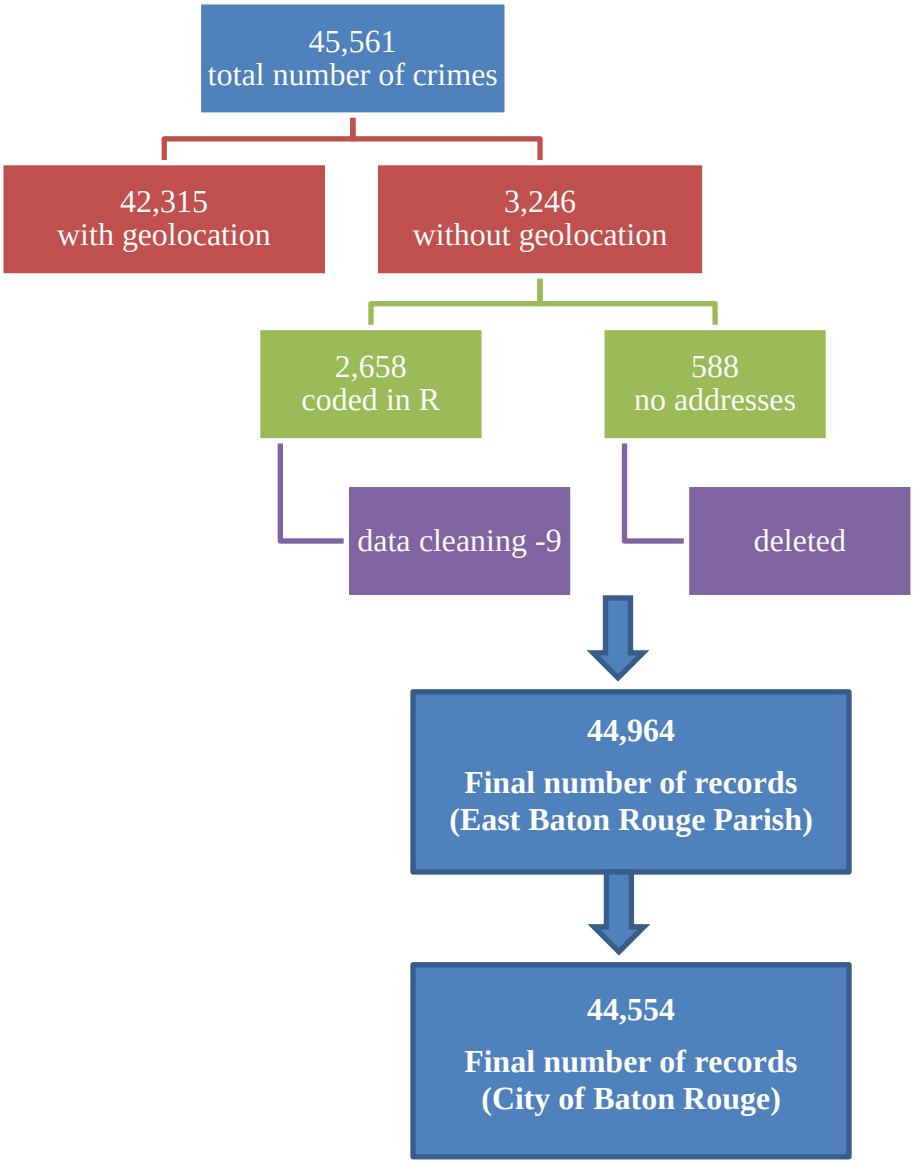


Figure 16. Data set preparation/cleaning of crime incidents for this research in the City of Baton Rouge (2018)

It should be noted that 97.7% of all crime records falling inside the EBRP could be geocoded. This means that the minimally acceptable geocoding match rate of 85% could be easily achieved.

5.2.2 Survey data

The survey includes (1) a background questionnaire about crime perception in the City of Baton Rouge and (2) an on-screen mapping exercise that is implemented in Google MyMaps. Participants were asked to draw a polygon around areas where they feel unsafe and to give a short description why they feel unsafe in that specific area. Each layer was saved as .kml or .kmz file and imported into ArcGIS. Different layers can be merged together in order to identify patterns and to compare survey results with field data results. The questionnaire is attached in Appendix A. Analyzing the data of the on-screen mapping exercise is not part of this thesis.

Two pre-tests were conducted, which took around fifteen minutes to be completed, including the questionnaire and the on-screen mapping exercise.

In March 2019, surveys were sent per email to Geography/Anthropology and Sociology students and non-student experts and locals participating in the geo-narrative field work. Test participants were asked to return the completed documents per email, as well.

5.3 Field work

5.3.1 Spatial video data collection

In total, 383.84 km were driven in 14 hours and 36 minutes split up over 8 days. The drives were conducted during daytime in good weather conditions without precipitations. During the drives, every street, except highways, were covered inside the five selected neighborhoods. The average speed was 26.29 km/h. High speed should be avoided due to impacts on the quality of video recordings. More detailed information of the distance, duration, and dates of the spatial video collection can be found in Table 4.

	Distance [km]	Duration [h:mm:ss]	Date
Fairfields	71.12 km	3:11:54	March 6th 2019; March 8th 2019; March 11th 2019
Mid City	122.02 km	4:29:06	March 11th 2019; March 13th 2019; March 18th 2019
Southside	56.4 km	2:03:00	March 25th 2019
Pollard/Woodchase	65.9 km	2:23:00	March 27th 2019
University Acres/Woodstone	68.4 km	2:29:00	March 22nd 2019
Total	**383.84 km**	**14:36:00**	**8 days**

Table 4. Distance, duration and dates of spatial video data collection

Some cameras, for unknown reasons, stopped recording after about 30 minutes. Therefore, before 30 minutes of recording were completed, cameras were turned off and on again in order to secure an appropriate data collection/storage. Two hours of driving took around 17 GB of memory space. Every second two GPS points were recorded.

5.3.2 Geo-narrative data collection

In total 46 geo-narratives were recorded over a 13-day timespan. Drives were from March 19th until April 18th, 2019 on mostly weekdays between 09:30 AM and 12:30 PM. Each drive on the pre-defined route with a length of 8.9 km took around 25 minutes depending on the traffic volume.

Participants were encouraged to verbally comment whether they perceived to be safe or unsafe in the area, where they are driving through, what their reasons were for feeling safe or unsafe, and if they have been in this specific area before. Additionally, the interviewer asked questions at specific points of interest, such as schools, convenient stores, the local bus station, etc. The entire conversation was recorded for further in-detail analysis.

5.4 Data processing of field work

5.4.1 Digitization

The digitization for one hour of drive in a neighborhood with many blight indicators took around 3 to 4 hours for each side of the street. In contrast, an area with few blight indicators took around 1.5 and 2 hours to digitize for each side. Recordings from the left- and right-hand sides had to be watched. In some cases, the front camera recordings had to be watched too for more detailed information. This means that the urban blight digitization process for a neighborhood with many indictors lasted for up to eight hours, and a neighborhood with few indicators for up to four hours, in total.

If a blight indicator was identified while playing/viewing the video recording, a point at the corresponding location on the map was created. Every point is assigned with a value in the attribute table, shown in Table 5. The attribute table includes the following attributes:

- ID
- Blight indicator (type and weight)
- Description (optional)
- Time stamp
- Date
- Camera
- Image
- Longitude
- Latitude

One blight location can consist of more blight indicators and can get a weight of 1 (low blight level), 2 (medium blight level) or 3 (high blight level), depending on the degree of blight. A "<Null>" means that a specific blight indicator does not occur. All different physical blight indicators defined in the criteria catalogue in Section 3.2 are listed in the attribute table using a short code, i.e. B1=abandoned building, B2=broken window/door, B3=blocked window/door, B4=no window/door, B5=building graffiti, B6=structural integrity, B7= building overgrowth, B8=other (building); E1=damaged sidewalk, E2=damaged road, E3=overgrown vegetation,

E4=litter, E5=illegal dumping, E6=unkempt area, E7=illegal parking, E8=abandoned vehicle, E9=infrastructural graffiti, E10=other. Since the majority of roads and sidewalks in Baton Rouge are damaged or sidewalks do not exist at all, these two variables are deleted from the attribute table. More detailed information about specific indicators is provided in the criteria catalogue in Section 3.2. Examples with photographs from the field work are shown in Appendix B.

FID	1582
Id	<Null>
B1	<Null>
B2	<Null>
B3	<Null>
B4	<Null>
B5	<Null>
B6	<Null>
B7	<Null>
E1	<Null>
E2	<Null>
E3	<Null>
E4	<Null>
E5	<Null>
E6	<Null>
E7	<Null>
E8	<Null>
E9	2
E10	<Null>
Descriptio	grafitti on garbage bin
time_stamp	13.3
Date	3/25/2019
Camera	southside_4_left
image2	
POINT_X	3335456.155824
POINT_Y	700692.654504

Table 5. Example of the attribute table with blight indicator information

5.4.2 Text mining

First, the recorded geo-narrative had to be transcribed into text. Navigation instructions of drives were not included in transcripts. Before performing text analysis, transcripts had to be cleaned. This means that irrelevant sentences were deleted from the transcript. Each spoken sentence was assigned a time stamp in the following format: [hh:mm:ss] in order to connect the text with the GPS point in the WordMapper software. An example of connecting the transcribed text with the

GPS track is shown in Figure 17. The pins on the map represent all sentences that are contained in the transcript. The yellow pin shows sentences that contain specific pre-defined keywords that are of interest for the research, such as safety, safe, unsafe, security, avoid, night, evening, comfortable, dark, blight, vacant lot, abandoned, trash, run down, familiar, bars, window, low income, poor, etc. By clicking a pin, the corresponding sentence appears. For example, in Figure 17 the sentence "Yes, that greyhound is very unsafe. I took it twice to go to New Orleans" pops up.

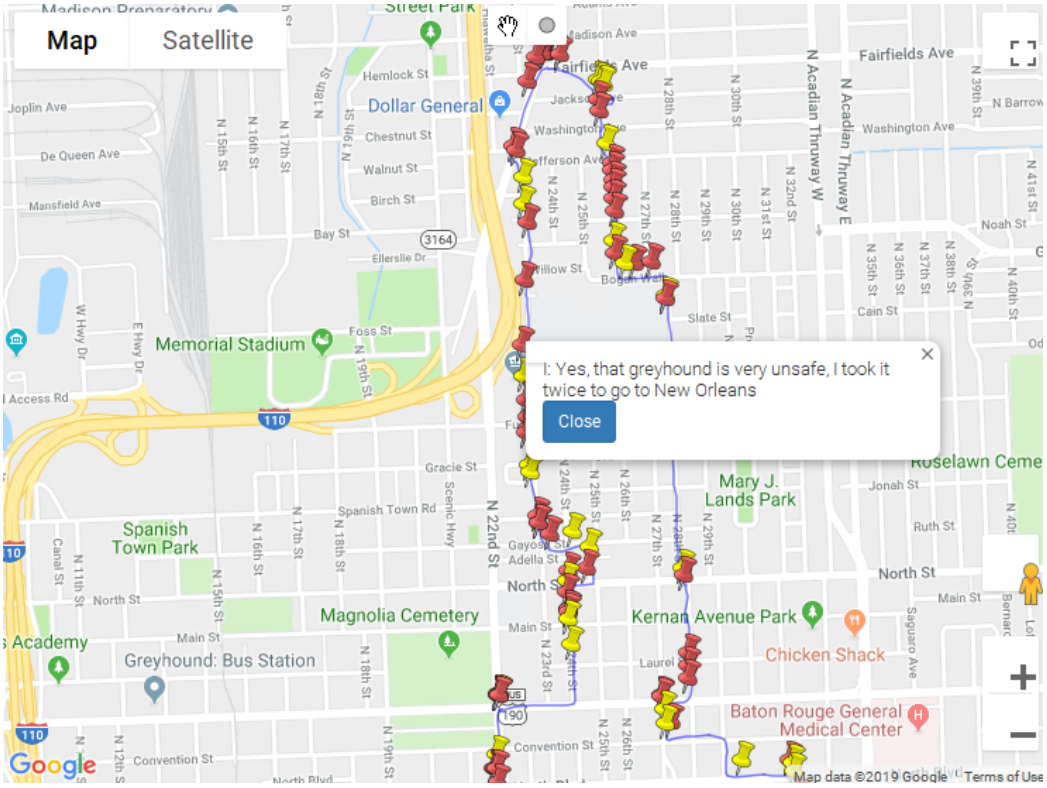


Figure 17. Sentences connected with GPS points

By finding the corresponding time stamp in the video recording an image can be viewed in order to better interpret given statements. Figure 18 shows the image associated with the selected sentence of Figure 17.

Figure 18. Corresponding image to the GPS point and spoken sentence highlighted in Figure 17

In the WordMapper software also categories can be defined, with which sentences can be assigned to. For the purpose of this research the following five categories were defined: (1) safety, (2) crime, (3) familiarity with the environment, (4) blight/condition, (5) wealth/status. Subsequently, the text of different geo-narratives was classified based on these five categories for qualitative text analysis. Subjective judgements based on the categories were extracted from transcripts.

Word clouds were generated to visually represent the text. The words are represented in different sizes, depending on the frequency of a specific word. Stop words that are not of interest for the analysis had to be defined, so they are not shown. Defined stop words for this analysis are for example: around, a, an, as, about, after, and, be, I, because, but, still, will, from, say, due, etc.

The Geo-SOM clustering algorithm trains neurons to find similarities in space and values of combinations between the five categories, including safety, crime, familiarity, blight/condition, wealth/status and their associated feelings, such as positive, negative, or neutral. In total there are 125 (5^3) possibilities of clustering. For this research eight clusters were generated using the k-means clustering algorithm.

Chapter 6

6 Results and Analysis

This Chapter aims to answer the research questions posed at the beginning of this thesis. Results of the spatial and statistical analyses of the collected urban blight data as well as the collected crime perception data with geo-narratives are presented. First, a series of descriptive statistics is calculated to identify distribution patterns and spatial clusters. Second, hot spot analysis, spatial autocorrelation, and clustering methods are carried out in a GIS environment. Finally, the data are compared with officially reported crime data to find correlations, applying Spearman's rank correlation. Only the most important results from the analysis are presented in this Chapter.

6.1 Spatial analysis of physical urban blight locations

6.1.1 Description of physical urban blight

In total, 1,717 urban blight locations are identified in the study area, with environmental/infrastructural blight accounting for 1,182 points (68.84%) of all locations. This is more than double the property blight locations with 538 points (31.16%). It should be noted that each location can have more than one blight indicators, for example, one building can have a broken window, a blocked window, and graffiti. Considering blight indicators separately, 880 property blight indicators and 1,498 environmental/infrastructural blight indicators are identified in the selected study area. The number of property blight indicators is illustrated in Figure 19 and the number of environmental/infrastructural blight indicators is illustrated in Figure 20. Overall, with 798 points litter is by far the most frequently occurring blight indicator. Considering property blight indicators, structural integrity and blocked windows/doors are the most common indicators. Broken windows/doors, building graffiti and building overgrowth occur least frequently. Overgrown vegetation, dumping, and unkempt areas are second to litter and among the most commonly environmental/infrastructural blight indicators.

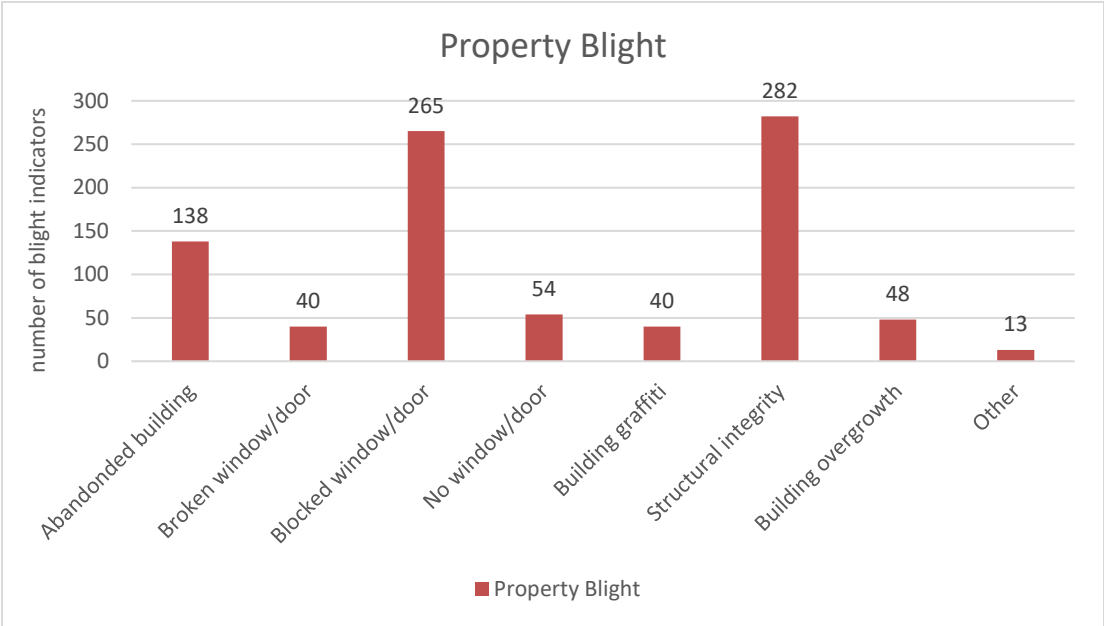


Figure 19. Frequency of property blight indicators

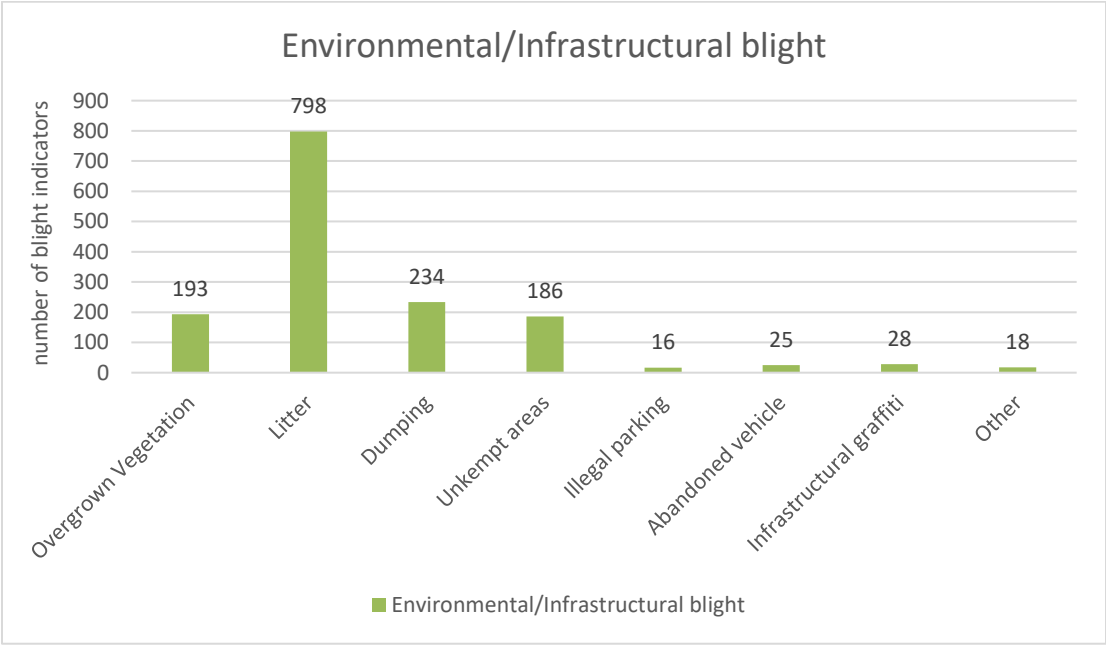


Figure 20. Frequency of environmental/infrastructural blight indicators

Looking at individual neighborhoods, Fairfields shows the most physical blight locations with a total count of 648 points, followed by Mid City with 692 points, Southside with 105 points,

Pollard/Woodchase with 49 points, and finally University Acres/Woodstone with 24 points. The distribution of physical blight locations across the five neighborhoods is shown in Figure 21.

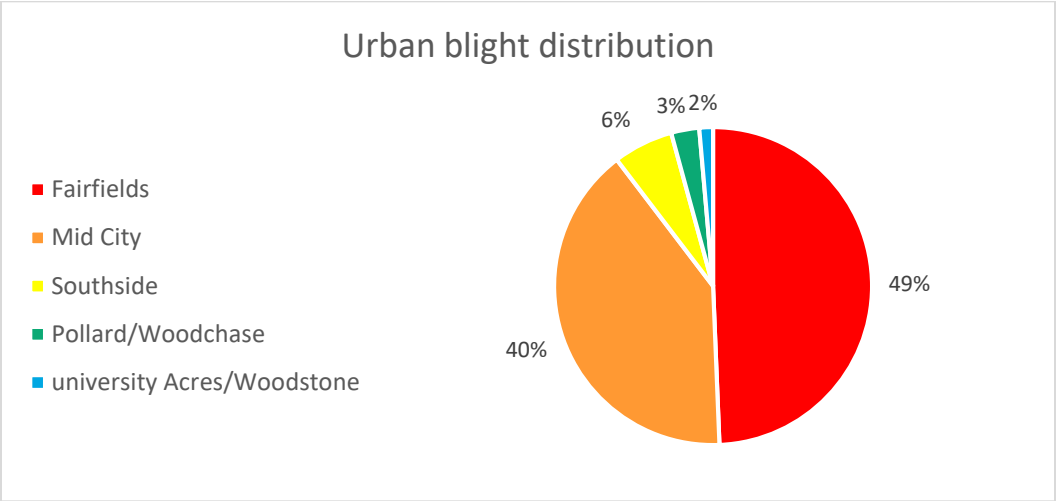


Figure 21. Urban blight distribution across selected neighborhoods (in %)

When looking at property blight and environmental/infrastructural blight separately, a very similar pattern can be detected (Figure 22). Fairfields has most property and environmental/infrastructural blight locations, followed by Mid City, Southside, Pollard/Woodchase, and University Acres/Woodstone.

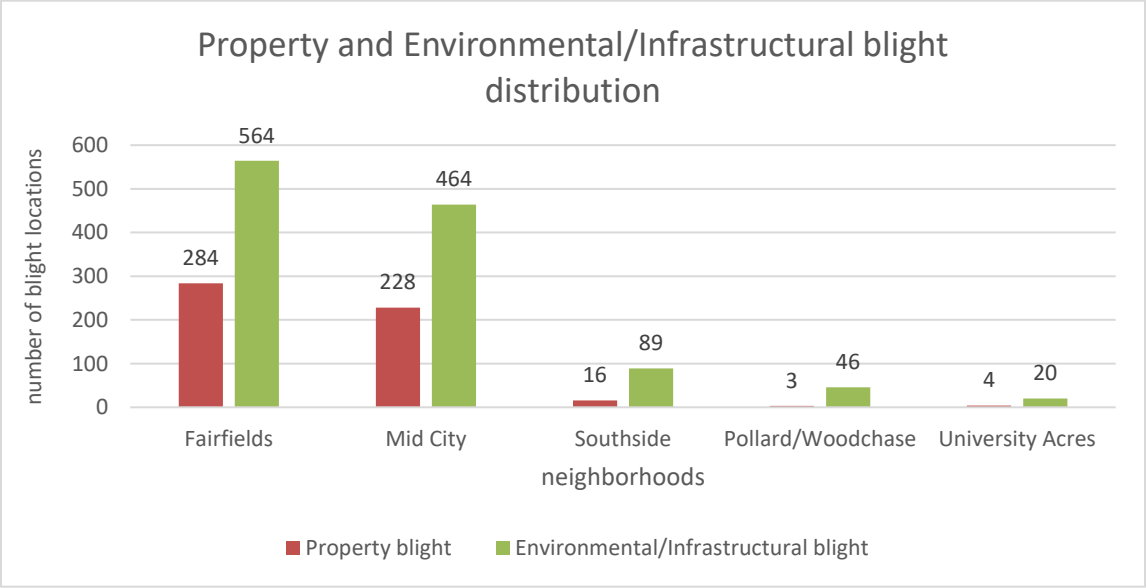


Figure 22. Count of property and environmental/infrastructural blight locations across selected neighborhoods

6.1.2 Distribution patterns of physical urban blight in the study area

Figure 23 visualizes the distribution of urban blight locations in the five selected neighborhoods. The red points indicate property blight locations, the green points present the environmental/ infrastructural blight locations. It is clearly visible that all points are concentrated in the northern neigborhoods, Fairfields and Mid City, and that environmental/ infrastructural blight locations are predominated.

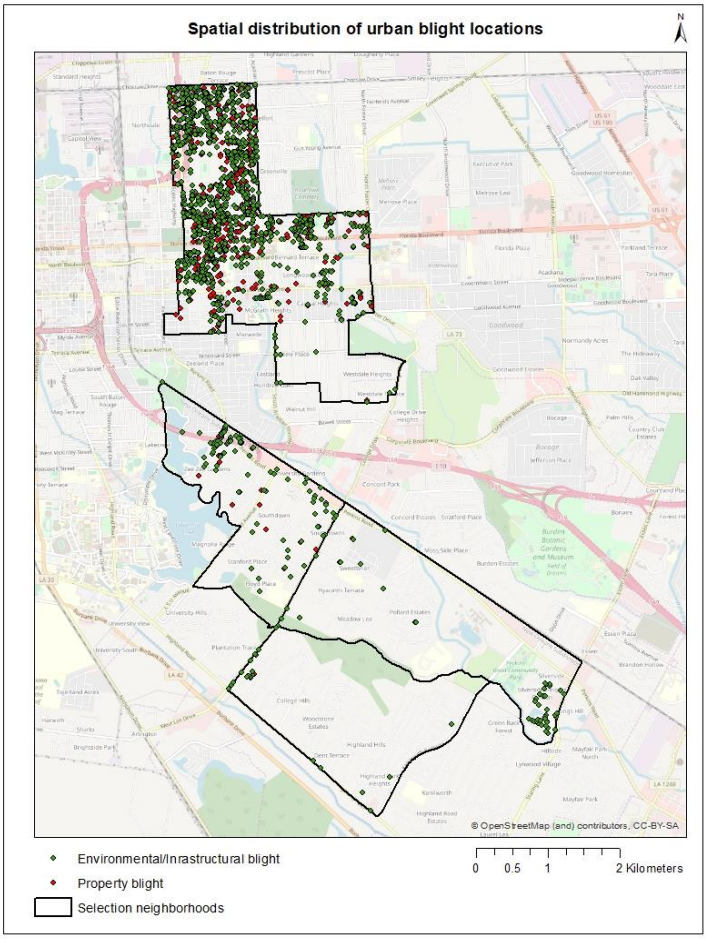


Figure 23. Spatial distribution of property and environmental/infrastructural blight locations across the five selected neighborhoods in Baton Rouge

The level of spatial dispersion of all blight locations is represented with standard deviational ellipses (SDEs), depicted in Figure 24. The red ellipse represents the one SDE for property blight and the green ellipse the one SDE for environmental/infrastructural blight. A north-south decrease

of points can be detected. Property blight locations are concentrated in a smaller area in Fairfields and in the northern part of Mid City, whereas environmental/infrastructural blight locations extend more into the southern part of Mid City. The spatial median of all blight locations is represented on the map in blue and is located on North Street, exactly at the border between Fairfields and Mid City.

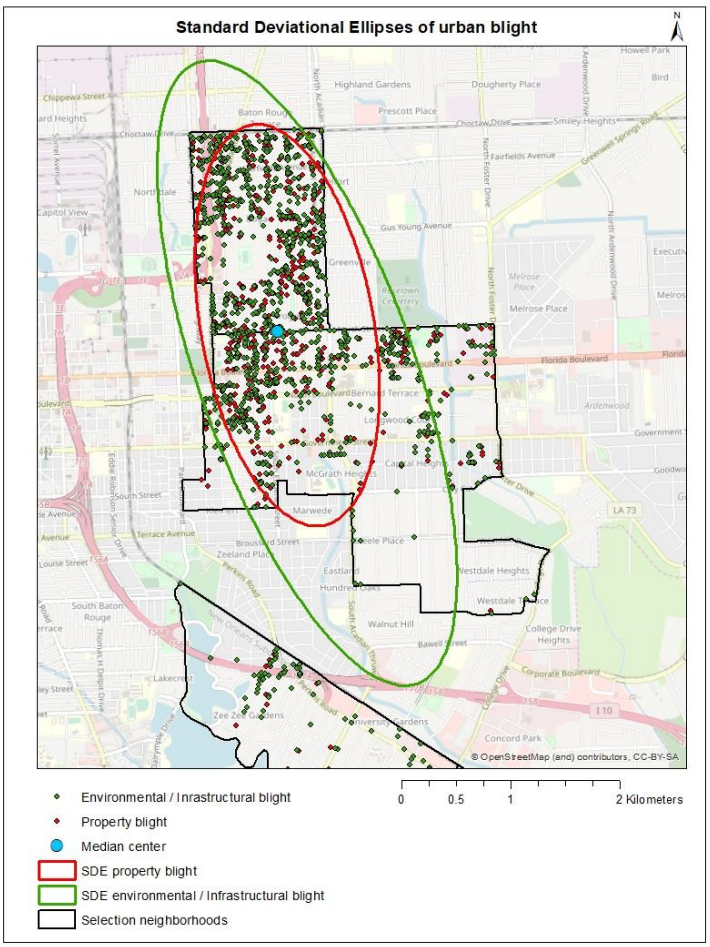


Figure 24. Median Center and one Standard Deviational Ellipses for property and environmental/infrastructural blight

Figure 25 shows one SDEs for different blight indicators for the three most occurring blight indicators for property blight (structural integrity, blocked window/door, abandoned property) and the three most occurring blight indicators for environmental/infrastructural blight (unkempt areas, litter, overgrown vegetation). All of these indicators are concentrated in similar areas in Fairfields, except abandoned properties that expand more into the south of the study area.

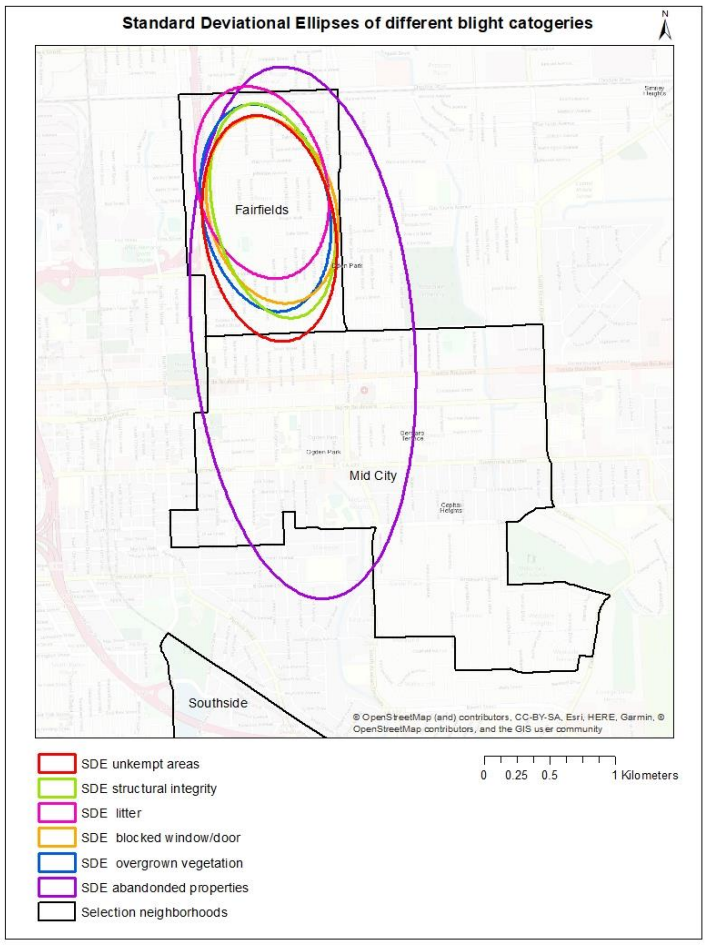


Figure 25. One Standard Deviational Ellipses for different blight categories

6.1.3 Spatial clusters of physical blight

The Moran's I value for urban blight locations is 0.62, which indicates that physical urban blight locations aggregated to census block groups show a positive spatial autocorrelation. The Moran's I scatter plot in Figure 26 between urban blight (x-axis) and spatially-lagged urban blight (y-axis) shows a regression line with the slope of this line corresponding to the Moran's I value. In this analysis, individual blight locations are aggregated into 22 census block groups and are represented on the horizontal axis, whereas the spatially lagged and aggregated blight locations are shown on the vertical axis. The spatial lag value represents the weighted average of the neighboring (i.e., census block group) values based on Queens's contiguity weights. Using Queens contiguity weights, neighbors are defined as spatial units sharing a common edge or a common vertex. The

Moran's I scatter plot can be divided into four quadrants showing spatial associations. The categories of these quadrants are Low-Low (LL) in the lower left, High-Low (HL) in the lower right, Low-High (LH) in the upper left, and High-High (HH) in the upper right in relation to the mean of both the aggregated blight and spatially lagged blight variables, defined by the vertical and horizontal interrupted lines in the graph. HH shows spatial clusters of similar values higher than the average and LL shows spatial clusters of similar values lower than the average. The category HL shows spatial outliers, where a high value is often surrounded by low values and LH shows spatial outliers where a low value is commonly surrounded by high values. The spatial association categories are represented in the cluster map in Figure 26.

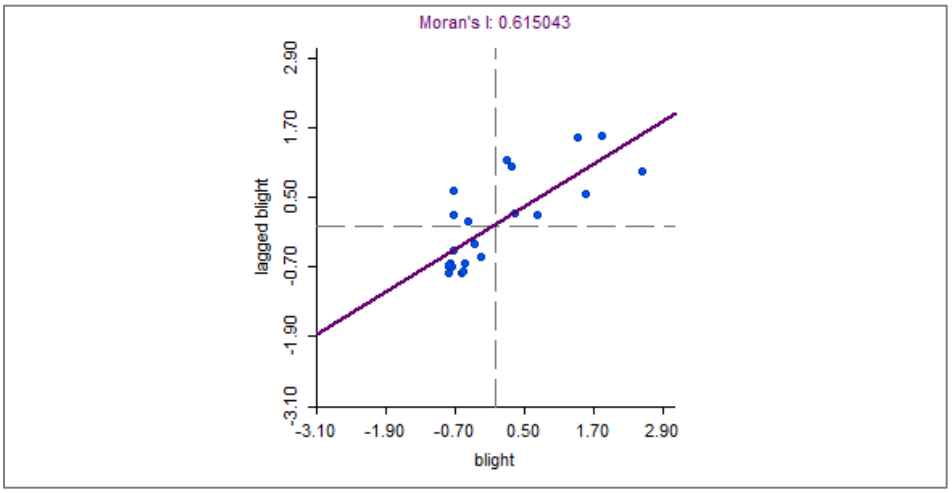


Figure 26. Moran's I value and scatter plot for urban blight aggregated to census block groups

The cluster map in Figure 27 shows the significant census block groups by its spatial association. The dark red color represents the High-High clusters (four census block groups fall into this spatial hot spot category) and are concentrated in the northern part of the study area. Dark blue represents the Low-Low clusters (six census block groups fall into this cold spot category) and are concentrated in the south. Low-High and High-Low spatial outliers do not exist.

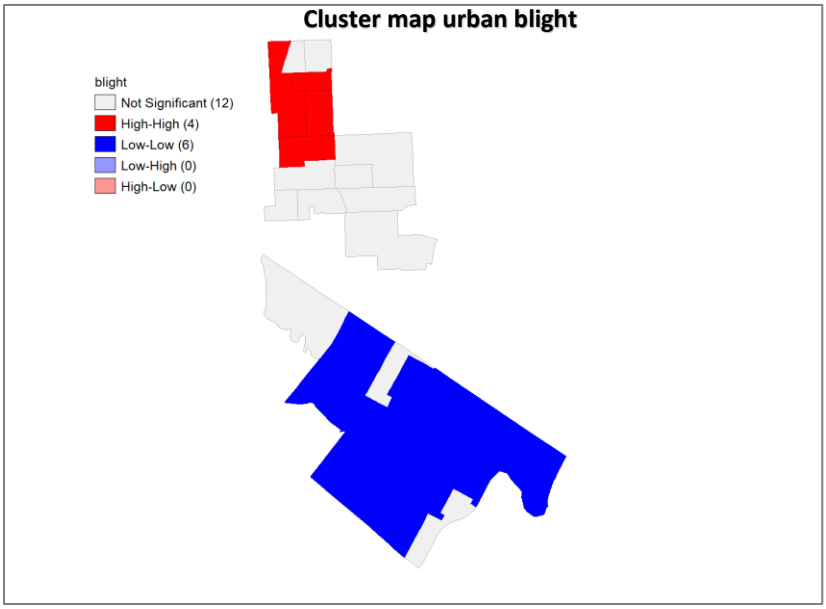


Figure 27. Cluster map of physical urban blight aggregated to census block groups

The Moran's I value in Figure 26 does not reveal information about its statistical significance. Its local statistical significance can be further explored in the significance map in Figure 28. The map shows census block groups with a significant local Moran's I value. The degree of significance is depicted in different shades of green. The lightest shade of green represents the largest p-value of 0.05 (five census block groups fall into this category), the darker shade of green represents a p-value of 0.01 (four census block groups fall into this category), and the darkest shade of green represents the smallest p-value of 0.001 (only one census block group falls into this category). Grey colored areas are not statistically significant.

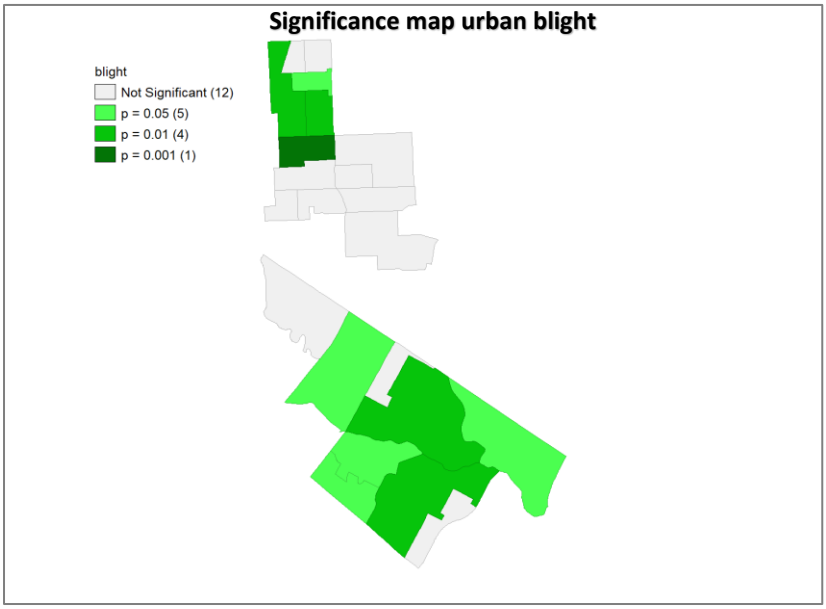


Figure 28. Significance map of physical urban blight aggregated to census block groups

6.1.4 Kernel density of physical blight

Figure 29 shows an (a) unweighted KDE for urban blight locations and a (b) weighted KDE for urban blight locations. Blight indicators for the weighted KDE have an intensity weight with the value 1 (low), (2) medium, or (3) high. For the unweighted KDE blight locations using boolean values are considered, where 1 indicates that blight exists and 0 indicates no blight. Values within a cell of 100*100 meters are summed up in order to calculate density values. Both KDEs use a normal Gaussian function. The planar method is used to measure the shortest distances between points. As for the classification method, quantiles are utilized, since the data are linearly distributed. Five classes are used, where each class contains an equal number of values. Red and orange show a high density of blight, and blue and green show a low density of blight. Comparing the unweighted and weighted KDE maps, similar patterns can be revealed.

a. b.

Figure 29. Kernel density estimation for (a) unweighted and (b) weighted physical urban blight

Figure 30 shows kernel density maps for different urban blight indicators. In this case unweighted values are used to calculate the KDE. The top three maps show property blight indicators that occur most frequently in the study area: (a) abandoned property, (b) blocked window/door, and (c) structural integrity. The bottom maps show the three most occurring environmental/infrastructural blight indicators: (d) dumping, (e) litter, and (f) overgrown vegetation. All KDEs apply the same parameters, namely a normal function and a cell grid size of 100*100 meters. Quantiles are used to classify the density values into five ranges, from very high blight (red) to very low blight (blue).

Abandoned properties, blocked windows and dumping show a very similar distribution and are mainly concentrated in Fairfields and in the northern part of Mid City. Litter, overgrown vegetation, and structural integrity of buildings is distributed across all neighborhoods within the study area, although most large hotspots can be found in Fairfields and in the northern part of Mid City.

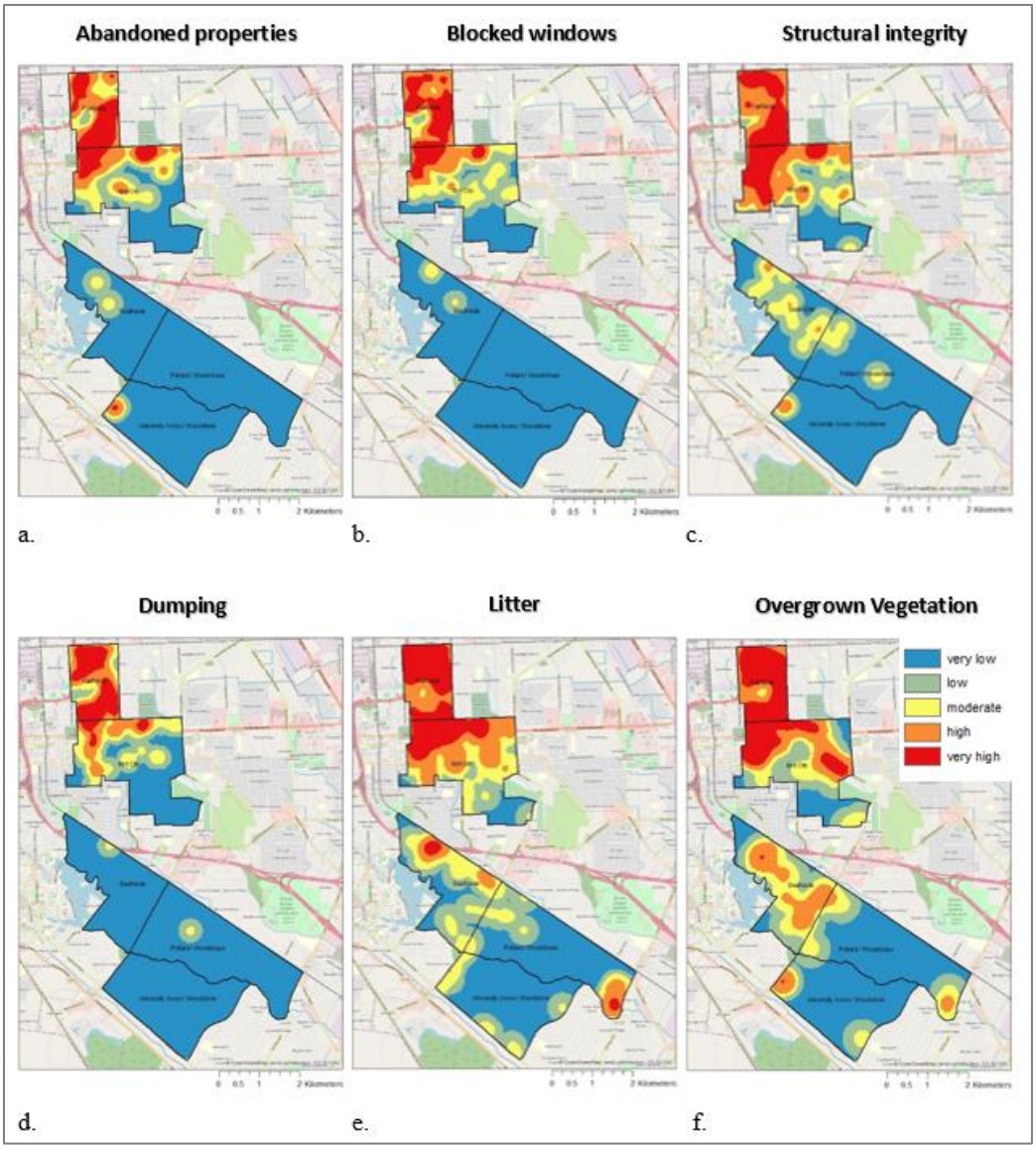


Figure 30. Kernel density estimations of different blight indicators: (a) abandoned properties, (b) blocked windows, (c) structural integrity, (d) dumping, (e) litter, (f) overgrown vegetation

The two heat maps in Figure 31 illustrate KDEs for (a) blight collected with the spatial video technology and (b) blight reported through 311 calls. The same parameters as previously applied to individual blight indicators (see Figure 30) are used. However, the data are normalized from 0-100 to compare the blight collected with the spatial video and the 311 self-reported blight data that are available from the Open Data Portal. It should be noted that the 311 data do not follow the same blight categories as employed in this study. The 311 data include broader categories that contain more blight indicators, for example recycling, sewer/wastewater, street/traffic issue, environmental

issues, blighted property, garbage etc. From the 311 indicators, environmental issues and blighted property are chosen as best matches to compare with the blight indicators used in this study. 708 reported blight locations could be identified from the 311 calls to be located in the selected study area. In comparison, 1,717 blight locations could be identified using the spatial video technology. Blight data collected with the spatial video shows more hotspots in Fairfields and Mid City, as compared to the 311 calls data set.

a. b.

Figure 31. Comparison of (a) blight data collected with spatial video and (b) 311 reported blight data

6.1.5 Urban blight index

The urban blight index provides evidence about the definition of blight as a whole. This means that it is determined, how many blight indicators within an area have to be present to conclude that the area can be considered as blighted. Census block groups are chosen as appropriate area within the scope of this study in order to determine the level of blight. The index compares the average local blight to other census block groups, an is visualized in Figure 32. The intensity of urban blight indicators is standardized utilizing a classification scheme depending on the severity of blight indicators within an area. Urban blight is standardized in five ranges from high (dark color) to low

(light color) using quantiles. Values in the legend are assigned to identify threshold standards for urban blight in Baton Rouge. If the blight intensity value is higher than 237 within a census block group, it can be considered as a high blight area. Moreover, weight measures of blight indicators (i.e., blight intensity) are considered in the urban blight index, since more broken windows in one house indicate a higher severity of blight than just one broken window.

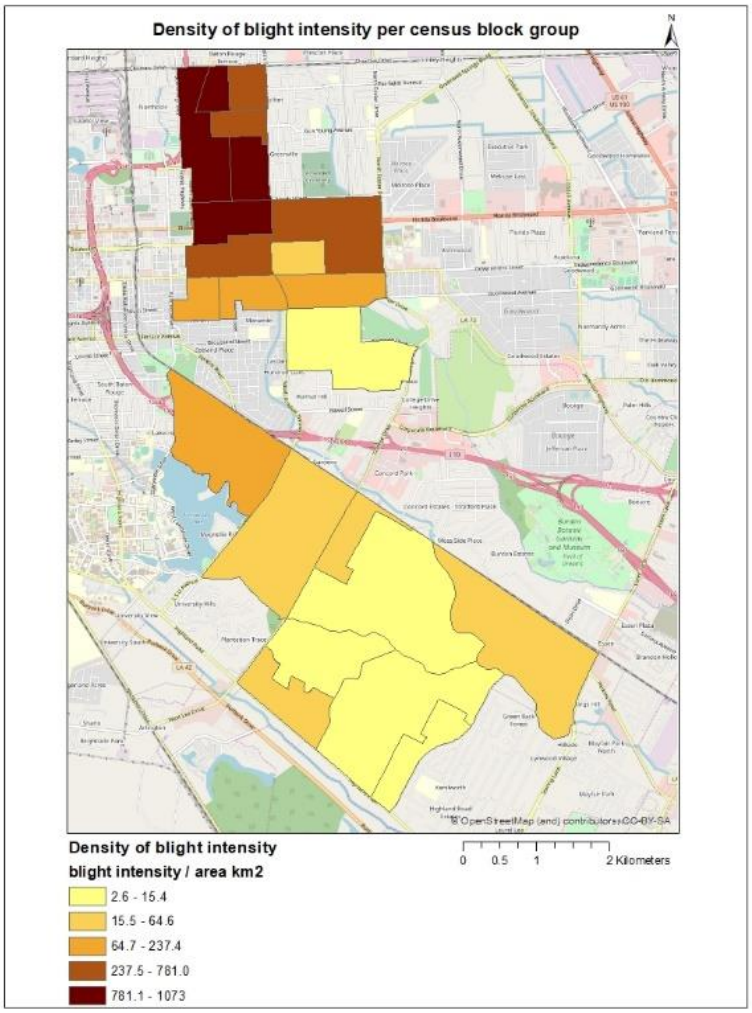
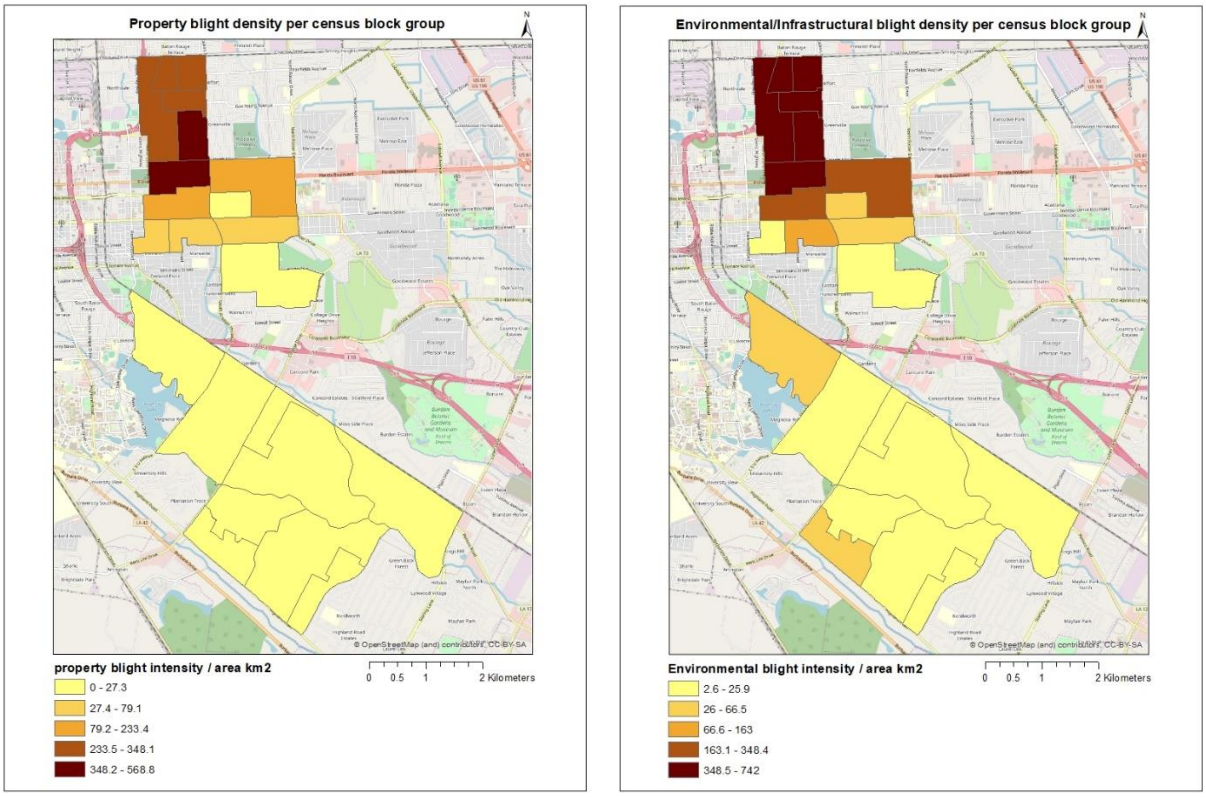


Figure 32. Density of blight intensity aggregated at the census block group level

The two maps in Figure 33 are constructed in the same way as the map in Figure 32, however, blight is separated into property blight and environmental/infrastructural blight. Occurrences of blight are again divided by the area. However, it could have been considered to divide property blight by the number of buildings and environmental/infrastructural blight by the street length, since data are collected by driving the street network within a census block group. Data from parks,

for example, are not collected but are included in the census block group. Moreover, the majority of properties is examined during the digitization process. However, by normalizing blight indicators with different variables (number of buildings, street length) the mapped results would not easily comparable.



a. b.

Figure 33. (a) Property blight intensity (b) and environmental/infrastructural blight intensity

6.2 Spatial analysis of crime

6.2.1 Description of crime types in the study area

Figure 34 provides an overview of the distribution of different crime types in the selected neighborhoods for 2018. Thefts are reported with a percentage of 26.5%, followed by burglary (14,9%), narcotics (9.1%), and criminal damage to property (8.0%). A more detailed description of all crime types is given in Section 3.1.

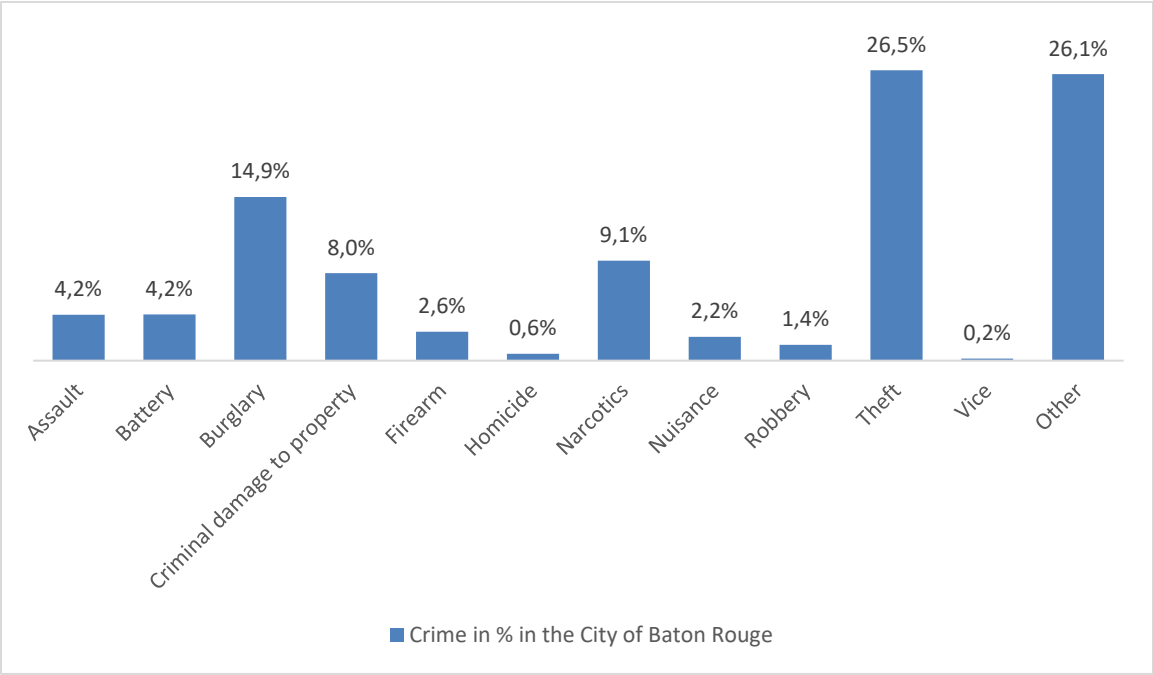


Figure 34. Percentage of crime types in the study area in 2018

Kernel density estimation for different crime types

Figure 35 shows a kernel density estimation of the four most occurring crime types in the year 2018 (burglary, criminal damage to property, narcotics, and theft). Homicides are also added, because they represent a severe problem in Baton Rouge. All five kernel density maps use the normal Gaussian function. The cell size for the output raster is set to 100*100 meters. The planar method is utilized to measure the shortest distances between points. As for the classification method, quantiles are used to divide density values into five class ranges, from very low (blue) to very high crime (red). Each class contains an equal number of values. By examining the spatial distribution across the different crime types, it can be determined that crime types are not homogeneously distributed. Homicides seem to almost exclusively concentrate in the northern part of the study area, namely in Fairfields and in the north of Mid City. Also, narcotics and criminal damage to property are highly concentrated in Fairfields and in the northern part of Mid City, but both crime types also show hotspots in Southside, Pollard/Woodchase, and University Acres/Woodstone in the south. Thefts and burglaries show multiple hotspots in southern neighborhoods, Southside, Pollard/Woodchase, and University Acres/Woodstone and are less concentrated in the north.

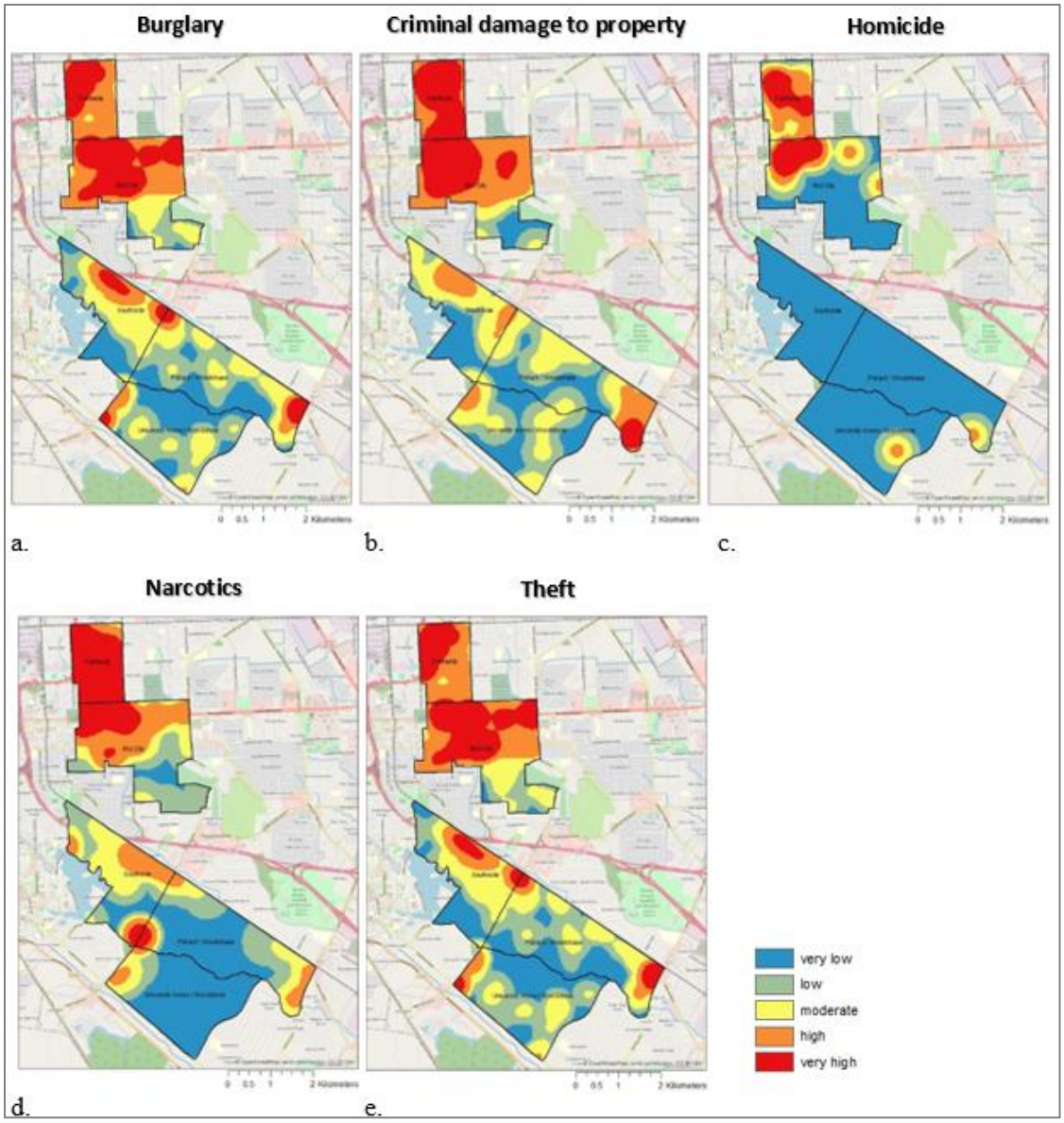


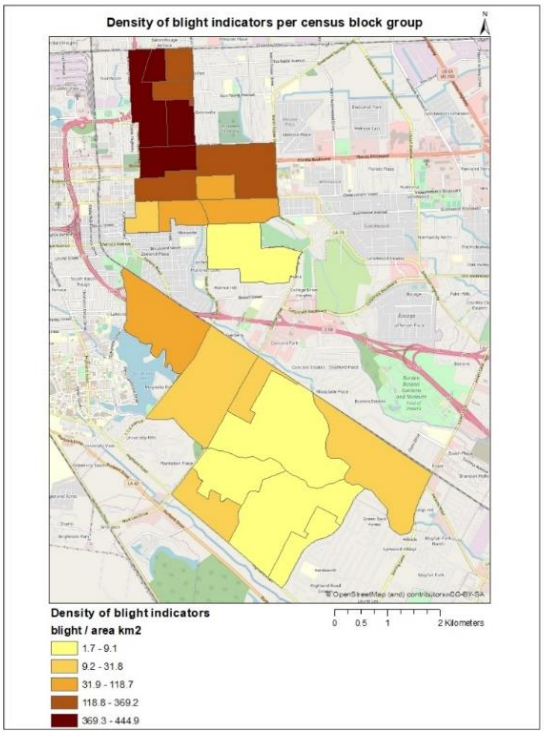
Figure 35. Kernel density maps of different crime types: (a) burglary, (b) criminal damage to property, (c) homicide, (d) narcotics, (e) theft

6.3 Relationship between physical urban blight and crime

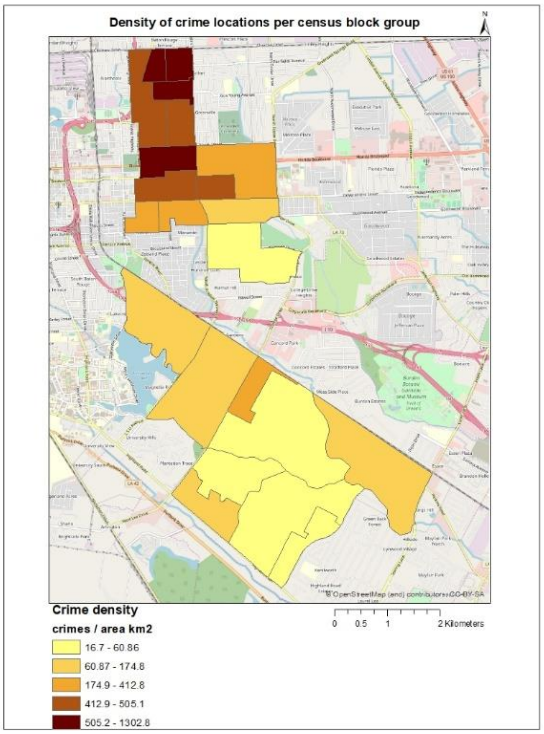
6.3.1 Density maps

The three maps in Figure 36 show (a) unweighted physical urban blight density, (b) crime density for the year 2018, and (c) median household income for the year 2018. Data are aggregated to census block groups. The number of crime and blight indicators within a census block group is divided by the area size to calculate the crime/blight density within a census block group. The quantile classification is used with a total of five classes. Light yellow indicates areas with low values of crime/blight/income, dark orange indicates census block groups with high values of crime/blight/income. A relationship between crime and blight can be identified. Results for median income are inversely distributed compared to both urban blight and crime. This indicates that blight and crime occur more frequently in low income areas and less frequently in high income areas.

It can be seen that there is a positive correlation between blight and crime, however, the visual comparison does not provide an objective or standard way about the degree of correlation between the two variables. In the next subsection the Spearman's Rank correlation method is applied to calculate statistical correlation values between different variables.



a.



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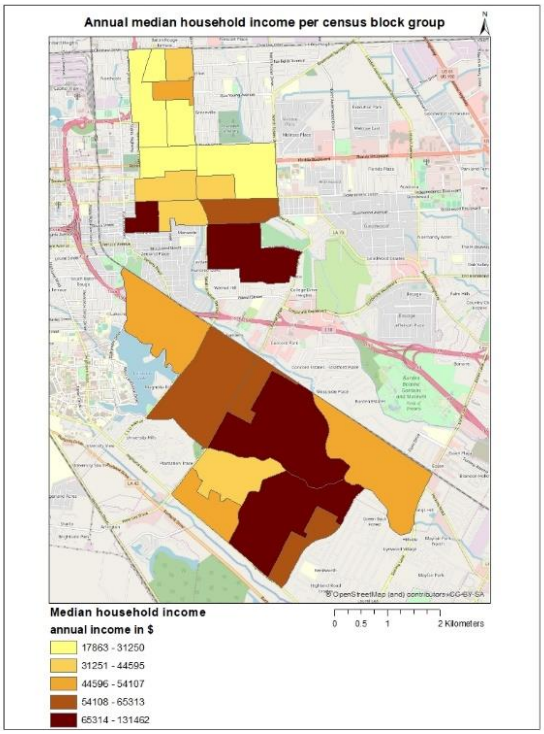


c.

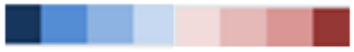
Figure 36. Relationship between (a) physical urban blight density, (b) crime density, and (c) median household income per census block group

6.3.2 Statistical relationships

The Spearman's rank correlation (rho ρ)) is used as a bivariate non-parametric method to measure the degree of linear relationship between blight and crime. The correlation is calculated based on the 22 census block groups contained in the study area. The resulting matrix in Table 6 shows correlation values between blight and crime, and between each individual urban blight indicator and crime type. The two-tailed level of statistical significance (p-value) is represented with stars behind the correlation coefficient. If the p-value is less than the significance threshold of 0.05, it is flagged with one star (*). If the p-value is less than 0.01, it is flagged with two stars (**). If the p-value is less than 0.001, it is flagged with three stars (***). Different shades of blue in Table 6 represent a positive relationship, the darker the shade the stronger the relationship. Red color would have indicated a negative correlation, but this type of correlation was not calculated. The non-colored values are statistically not significant.

By exploring Table 6 it can be established that only positively correlated values can be found. The Spearman's value for blight and crime is 0.81*** and indicates a strong positive correlation between the two variables. For individual crime types, battery and narcotics show the highest correlation coefficients with different urban blight types. The individual blight type litter is strongly correlated with different crime types. Most correlation coefficients for vice, illegal parking and infrastructural graffiti are not significant.

	All crime types	Assault	Battery	Burglary	Criminal damage to property	Firearm	Homicide	Narcotics	Nuisance	Robbery	Theft	Vice
All blight indicators	0.81***	0.79***	0.92***	0.42 n.s.	0.80***	0.73***	0.67***	0.89***	0.79***	0.78***	0.56**	0.30 n.s.
Abandoned property	0.71***	0.70***	0.85***	0.33 n.s.	0.71***	0.67***	0.65**	0.84***	0.76***	0.78***	0.46*	0.25 n.s.
Broken window	0.64**	0.64***	0.84***	0.19 n.s.	0.57**	0.63**	0.58**	0.83***	0.57**	0.67***	0.46*	0.16 n.s.
Blocked window	0.70***	0.73***	0.85***	0.24 n.s.	0.73***	0.72***	0.77***	0.88***	0.74***	0.74***	0.43*	0.21 n.s.
No window	0.61**	0.67***	0.81***	0.28 n.s.	0.65**	0.67***	0.52*	0.75***	0.62**	0.67***	0.37 n.s.	0.19 n.s.
Building graffiti	0.66***	0.58**	0.81***	0.46*	0.60**	0.48*	0.38 n.s.	0.71***	0.64**	0.60**	0.43*	0.18 n.s.
Structural integrity	0.75***	0.77***	0.80***	0.44*	0.79***	0.66***	0.68***	0.75***	0.80***	0.77***	0.54**	0.34 n.s.
Building overgrowth	0.51*	0.63**	0.74***	0.29 n.s.	0.61**	0.59**	0.44*	0.66***	0.47*	0.54**	0.22 n.s.	0.02 n.s.
Overgrown vegetation	0.76***	0.72***	0.85***	0.42*	0.69***	0.64**	0.58**	0.82***	0.67***	0.64**	0.49*	0.25 n.s.
Litter	0.92***	0.84***	0.93***	0.51*	0.87***	0.76***	0.69***	0.87***	0.89***	0.86***	0.72***	0.46*
Dumping	0.65**	0.70***	0.86***	0.27 n.s.	0.66***	0.69***	0.57**	0.82***	0.64**	0.70***	0.42 n.s.	0.21 n.s.
Unkempt area	0.68***	0.71***	0.86***	0.28 n.s.	0.68***	0.68***	0.62**	0.84***	0.64**	0.69***	0.40 n.s.	0.13 n.s.
Illegal parking	0.20 n.s.	0.37 n.s.	0.48*	-0.03 n.s.	0.34 n.s.	0.46*	0.32 n.s.	0.45*	0.26 n.s.	0.38 n.s.	-0.06 n.s.	-0.12 n.s.
Abandoned vehicle	0.60**	0.64**	0.74***	0.39 n.s.	0.60*	0.61**	0.36 n.s.	0.65**	0.50*	0.50*	0.40 n.s.	0.24 n.s.
Infrastructural graffiti	0.39 n.s.	0.20 n.s.	0.43*	0.42 n.s.	0.26 n.s.	0.15 n.s.	-0.03 n.s.	0.32 n.s.	0.08 n.s.	0.17 n.s.	0.19 n.s.	-0.21 n.s.



Positive correlation Negative correlation

* <0.05 ** <0.01 *** <0.001 n.s. not significant

Table 6. Spearman correlation coefficients between blight indicators and crime types aggregated by census block groups (n=22)

The graph in Figure 37 depicts the relationship between all crime and all blight types for each of the 22 census block groups. As shown in the correlation matrix in Table 6 these two variables are strongly positively correlated with each other and possess a coefficient of 0.81. This can be confirmed by looking at the trend line in Figure 37, where the blue line illustrates the number of all crime types and the red line the number of all blight indicators for the 22 census block groups on the x-axis and the normalized value of all crime/blight locations using the min-max normalization on the y-axis. It is clearly shown in this figure that the two variables tend to follow similar patterns across the census block groups.

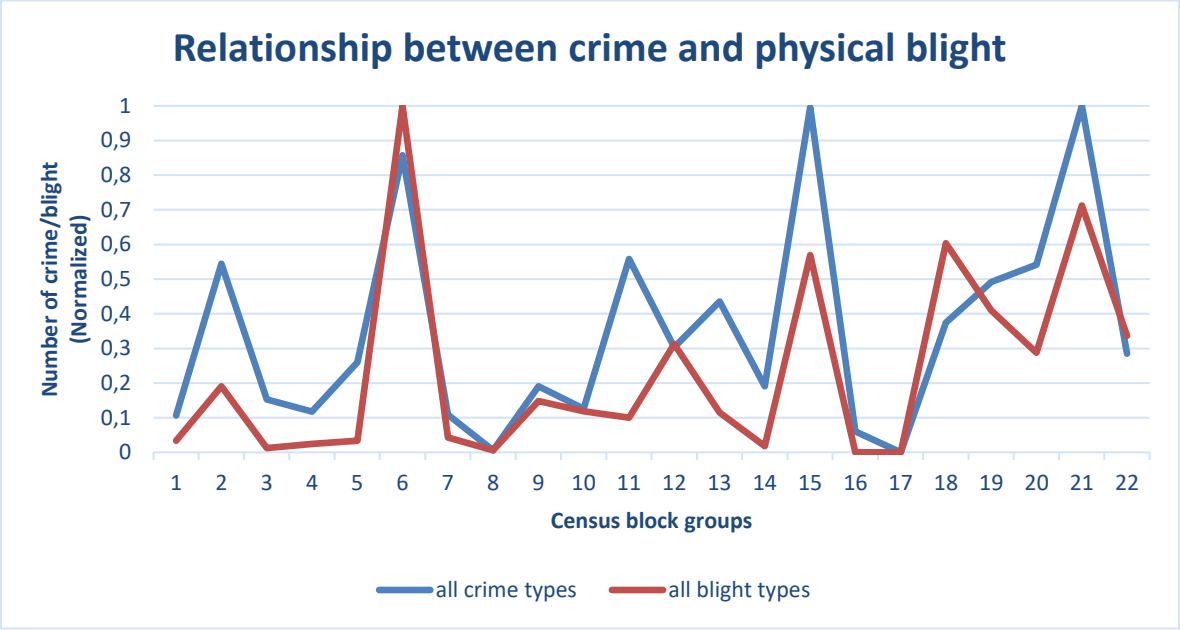


Figure 37. Relationship diagram between crime and physical blight based on census block groups

6.4 Spatial analysis of perceived crime

6.4.1 Survey results

The pie chart in Figure 38 shows the answers of 53 participants to the survey question: “How safe do you feel in Baton Rouge, in general?”. It can be determined that almost half of the participants answered the question with “moderate”. 33% of the participants answered to feel “safe” in Baton Rouge. Another 11% said that they feel “unsafe”. Only a few of the participants feel “very unsafe” or “very safe” in Baton Rouge.

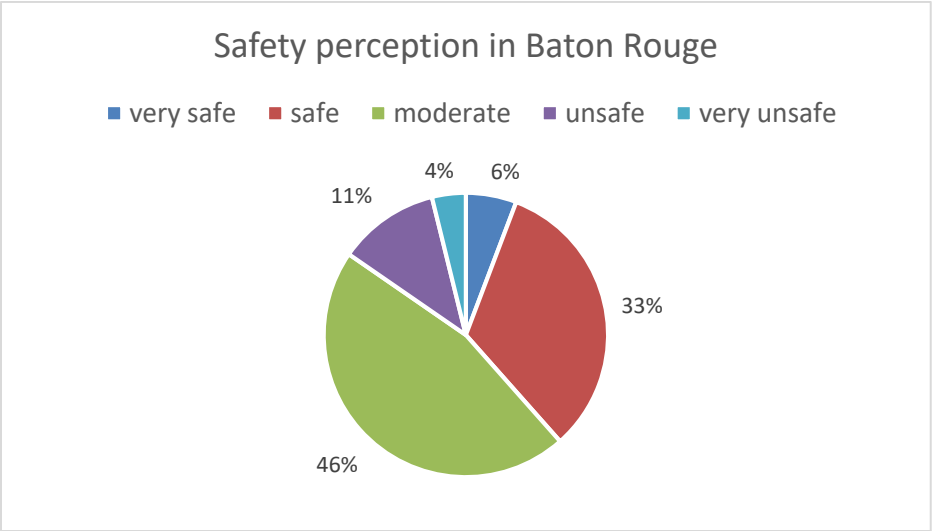


Figure 38. Safety perception in Baton Rouge (n=53)

Out of the 53 participants, 48 say that they feel unsafe during the night. 9 participants have been the victim of a crime, i.e. robbery, car burglary, theft, and sexual assault.

Figure 39 visualizes the distribution of answers to the question: “How does urban blight influence your perception of safety?” Almost half of the test persons answered this question with “medium”, 38% have the opinion that blight influences the perception of safety a lot. 9% of participants think that blight only influences the perception of safety slightly, whereas 9% think that blight does not influence the perception of safety at all.

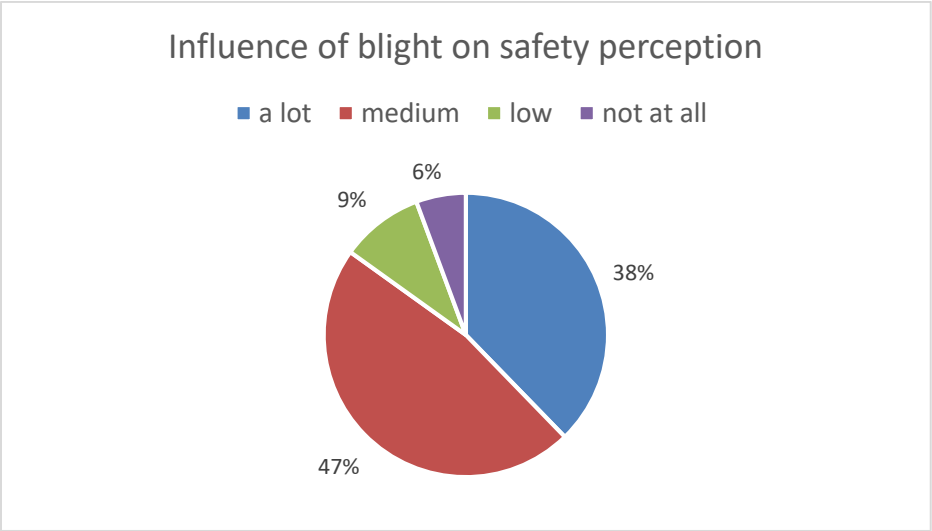


Figure 39. Influence of blight on safety perception (n=53)

6.4.2 Qualitative text analysis visualized on maps

In the following, the qualitative analysis is exemplary carried out for one student, one local stakeholder, and one expert. The analysis of all participants will be completed in future research. Statements made by these three participants that aim to answer questions such as “How does the environment influence your perception of crime?” or “When and where do emotions of fear arise?” are displayed in the maps in Figure 40 (student), Figure 41 (local stakeholder), and Figure 42 (expert). The color of point symbols represents the feeling associated with the sentence. Red means a negative feeling, yellow a neutral feeling, and green a positive feeling. It should be noticed that the study area is north and south of Government Street, which is the border line between high crime (north) and low crime (south), and between low income (north) and middle-income (south) areas.

Figure 40 shows the map with selected sentences of a male student, who is not familiar with most of the area north of Government Street. It is remarkable that the student gets slightly nervous if he sees a sign with the word “neighborhood watch”. The student considers it as a sign “to aware people to be checking their surroundings, thieves could be around the area”. He mentions that by seeing the warning sign he would not feel safe in the area. Moreover, the student mentions that he feels safer in residential areas than in commercial areas. Areas around educational institutions are unsafe in his opinion. He thinks that crime occurs more often around educational institutions because “young students are easy targets for thieves”. The student notices that the northern part looks underdeveloped and relates it to low income. Abandoned houses attract criminals, drug trafficking and homeless people. In general, because he is “a male and less target for thieves” he would not feel unsafe during the day, however he prefers to avoid the northern part of Government Street, especially during the night. In the southern part of Government Street, the student feels more positive. He says that it is a middle-class area, where houses are bigger, and where ”people feel safe leaving their cars outside, with no fear of them getting vandalized”.

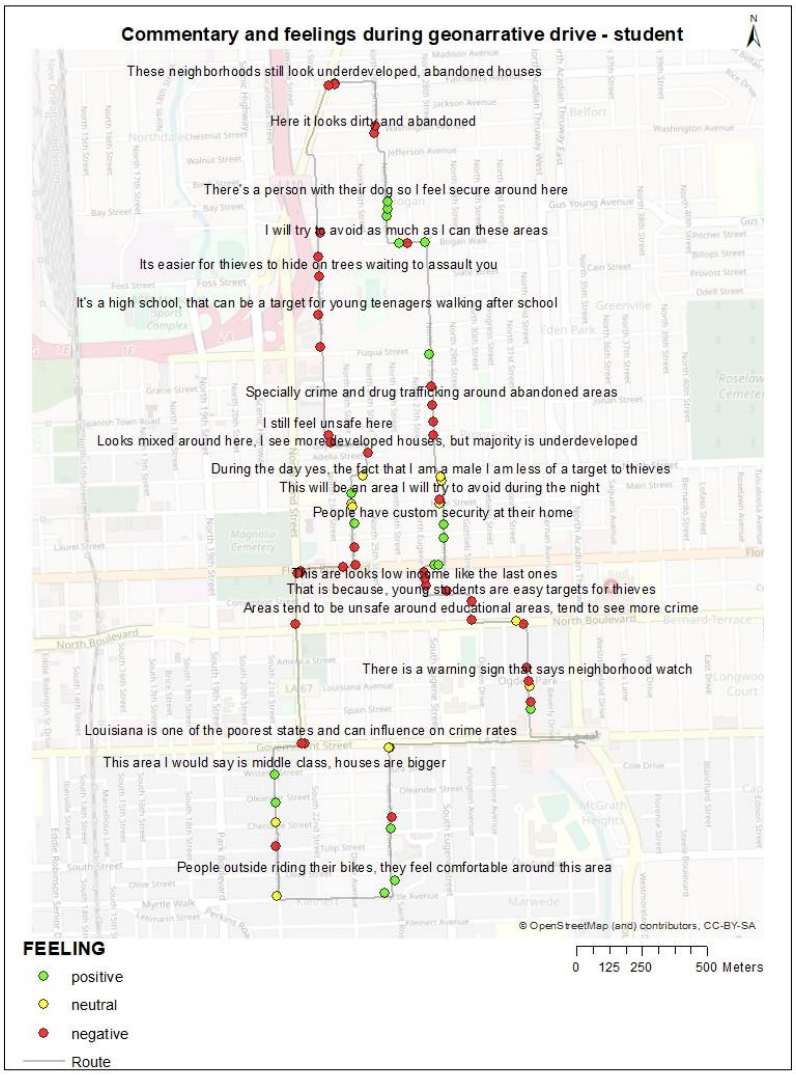


Figure 40. Example of individual geo-narrative sentences made by a student

Remarkable statements of the local stakeholder are shown in Figure 41. The local is in contrast to the student more familiar with the area. He has lived in Baton Rouge since 1976. He mentions that the area immediately north of Government Street is gentrifying: “You gonna find young people coming in and buy in this area you know.” He says that the northern part used to be a nice neighborhood one time, “but as the city moved, these neighborhoods began to deteriorate”. Now the neighborhood is characterized by abandoned houses and people with low income living in this northern area. He says that low income “creates an environment of some hopelessness, desperation”. “And those two things start contributing to crime, drugs, and things like that”. He thinks that a specific group of people do not care about their properties and surroundings, but that

“does not mean that every low-income area, everybody does not care”. He thinks that the northern part is a high crime area, however, robberies are not a problem, since people living in these areas do not have a lot of valuables in their houses. He thinks that physical abuse and sexual abuse are more problematic in the neighborhood than burglaries and robberies. In sum, the local stakeholder does not particularly feel unsafe in the northern part of the test area, but he thinks that some of the houses need repair. The neighborhood south of Government Street is well-kept and rising in value. He is familiar with the area. He has a house there and family lives in one of the streets immediately south of Government Street. The local feels safe in this area, however he knows from experience that also robberies and battery happen in the southern part.

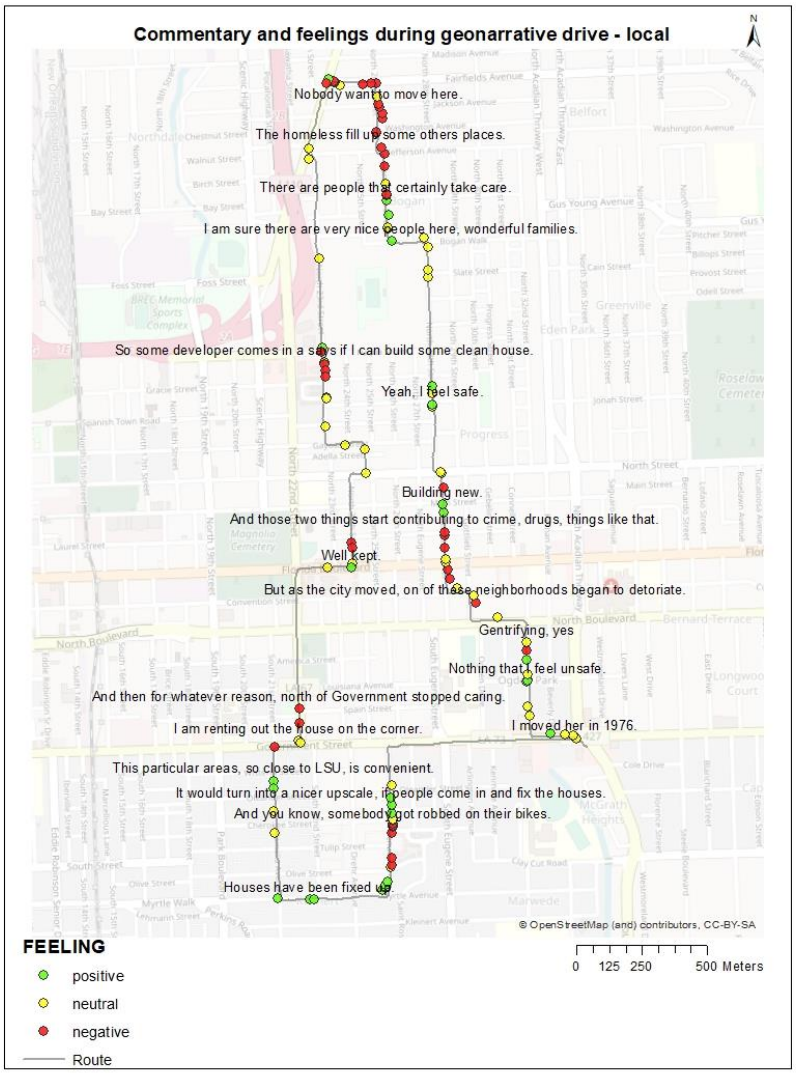


Figure 41. Example of individual geo-narrative sentences made by a local stakeholder

The third test person (Figure 42) is working for the Baton Rouge Council and is an expert dealing with the issue of blight and re-development in North Baton Rouge. He grew up in Baton Rouge. He is very familiar with the area north of Government Street, since his family used to live there. It used to be a nice neighborhood where mainly the working class was concentrated. Starting from the 1950s, when the population in Baton Rouge began to grow, the status and condition of the neighborhood began to change. Indicators of blight started to increase. He says that people who now grow up in these areas do not care, if their property is in a bad condition or if there is trash on the streets. He remarks that the City of Baton Rouge has programs to clean up debris and dumpings, and that the City is investing in some of the areas, however it is diffucult to target the whole area. Regarding the safety perception, the test person mentions that he would feel safe to walk around in this neighborhood, however if people would hang out on the street in groups and looking at him, he would not feel comfortable anymore. He mentions that he might perceive crime in Baton Rouge different from other people, since he is familiar with the crime statistics. In contrary to the majority of the test persons, he thinks that Florida Bouleverd instead of Government Street is the border line between poverty areas and middle income areas. He thinks that ”through decades maybe that line between north and south is a little bit shifted this way or that way”. Government Street is changing, a lot of reconstruction is going on. In his opinion the area south of Government Street, the “Garden District” is “one of the nicest in Baton Rouge”. Another remarkable statement is the fact that “the police force has not been increased since the 1980s”, however “the city has grown exponentially”.

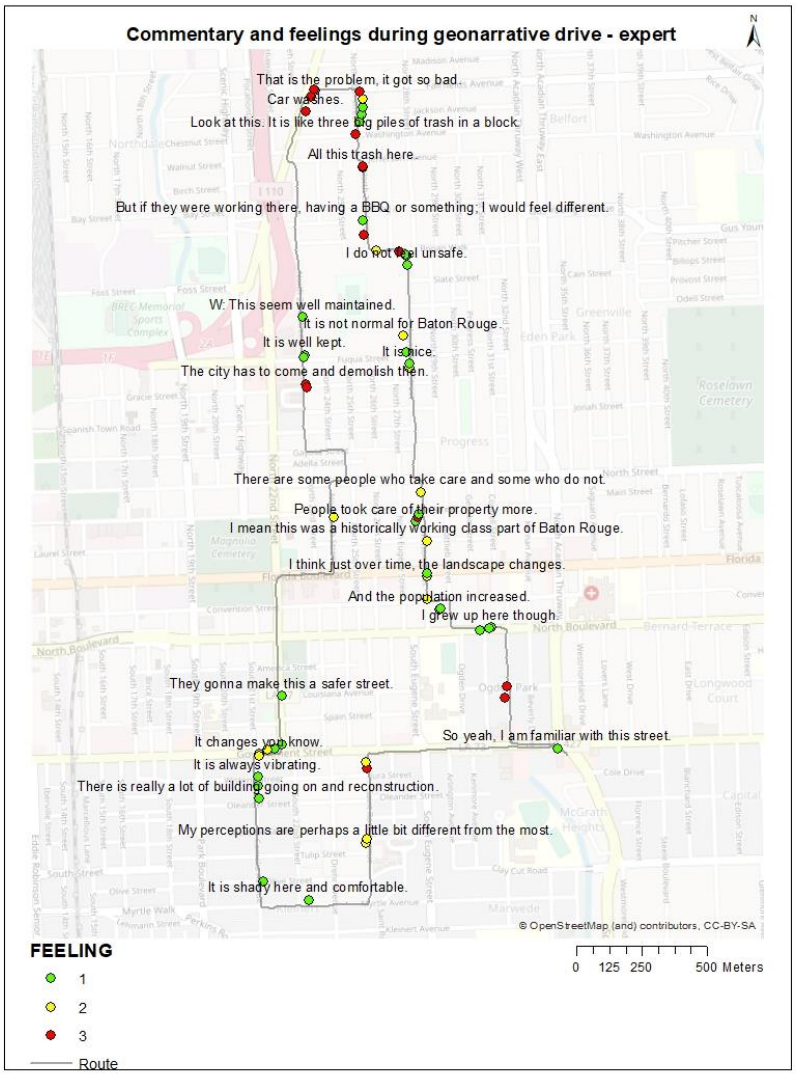


Figure 42. Example of individual geo-narrative sentences made by an expert

The map in Figure 43 illustrates the relationship between actual crime locations and perceived crime according to the three test persons that were considered for this analysis. Actual crime areas are illustrated utilizing a kernel density map in the background applying the quantile classification method divided into 5 classes, where red and orange illustrates high crime areas and blue and green low crime areas. Point symbols illustrate the feeling of the three test subjects based on sentences that belong to the category safety, crime, familiarity, blight/condition, and status/wealth. Green points indicate a positive feeling, yellow a neutral feeling, and red a negative feeling. Results of the three test subjects are merged together to identify areas, where people perceive to be unsafe considering criminal activities. It can be noted that the area south of Government Street shows the

most points associated with positive feelings. In the area north of Government Street mixed feelings occur, whereas the northern and western part of the route have the most sentences associated with negative feelings.

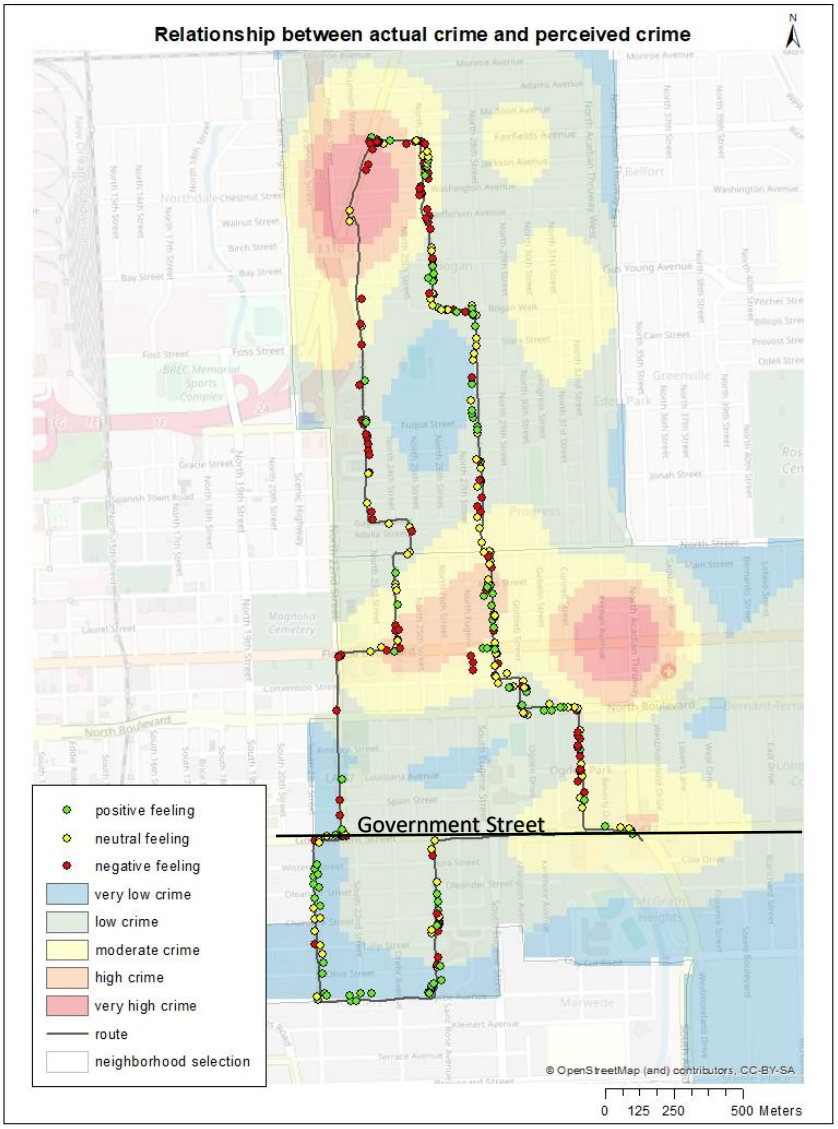
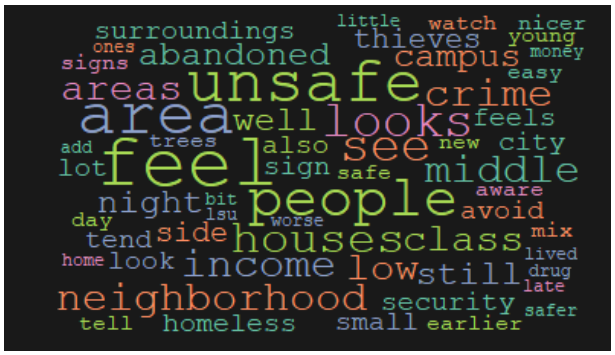


Figure 43. Relationship between actual crime and perceived crime considering statements made from three test subjects

6.4.3 Word clouds

Figure 44 shows the resulting word clouds for (a) the student, (b) the local stakeholder, and (c) the expert. The words “feel” and “unsafe” are highlighted for the student and expert. Moreover, the words “people”, “trash”, “crime, “houses, “familiar”, and, “government” are also highlighted in all three word clouds.

Student



a.

Local stakeholder

b.

Expert

c.

Figure 44. Word clouds representing commentary of (a) a student, (b) a local stakeholder, and (a) an expert

6.4.4 Geo-SOM

Figure 45 shows the resulting Geo-SOMs for (a) the student, (b) the local stakeholder, and (c) the expert. Eight clusters are defined using inverse distance to create the distance matrix between neurons of the categories safety, crime, familiarity, blight/condition, and status/wealth. The k-means algorithm is used for clustering.

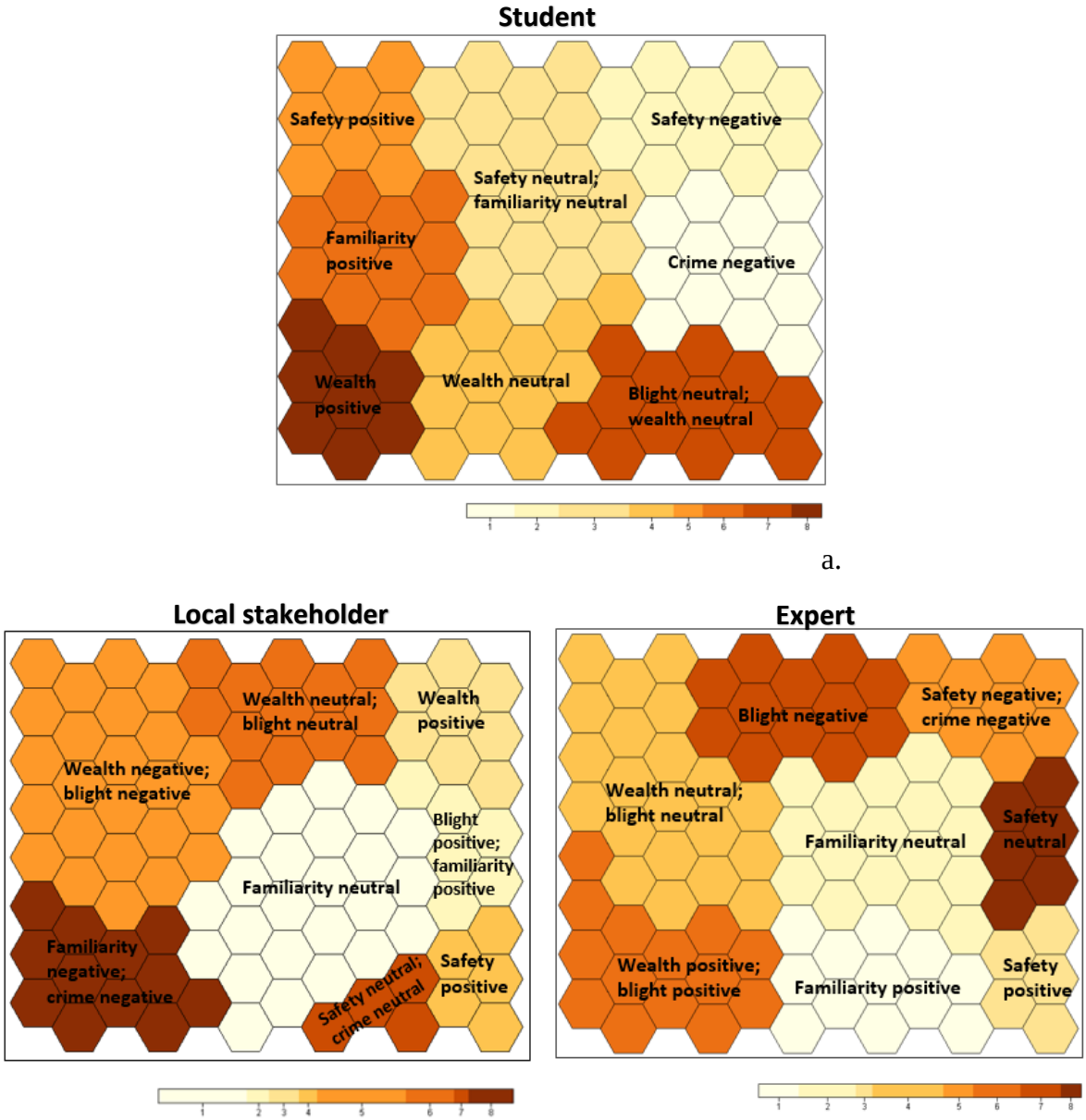


Figure 45. Geo-SOM clustering categories and feelings from commentaries of (a) a student, (b) a local stakeholder, and (c) an expert

Different clusters are created for each case depending on the similarity between the variables in value and space. The bigger the cluster, the more often the combination of the variables occurs. One cluster can consist of more combinations. For the student the biggest cluster consists of the variables “safety neutral” and “familiarity neutral”. For the local stakeholder the combination “wealth negative” and “blight negative” forms the biggest cluster, whereas for the expert “wealth positive” and” blight positive” forms the biggest cluster.

The clusters can be visualized in a map, because the Geo-SOM algorithm for creating clusters also considers space. Figure 46 shows an example how the Geo-SOM can be visualized in a map. The following three clusters are chosen to be illustrated in the map: (1) crime negative, (2) safety negative, and (3) safety positive.

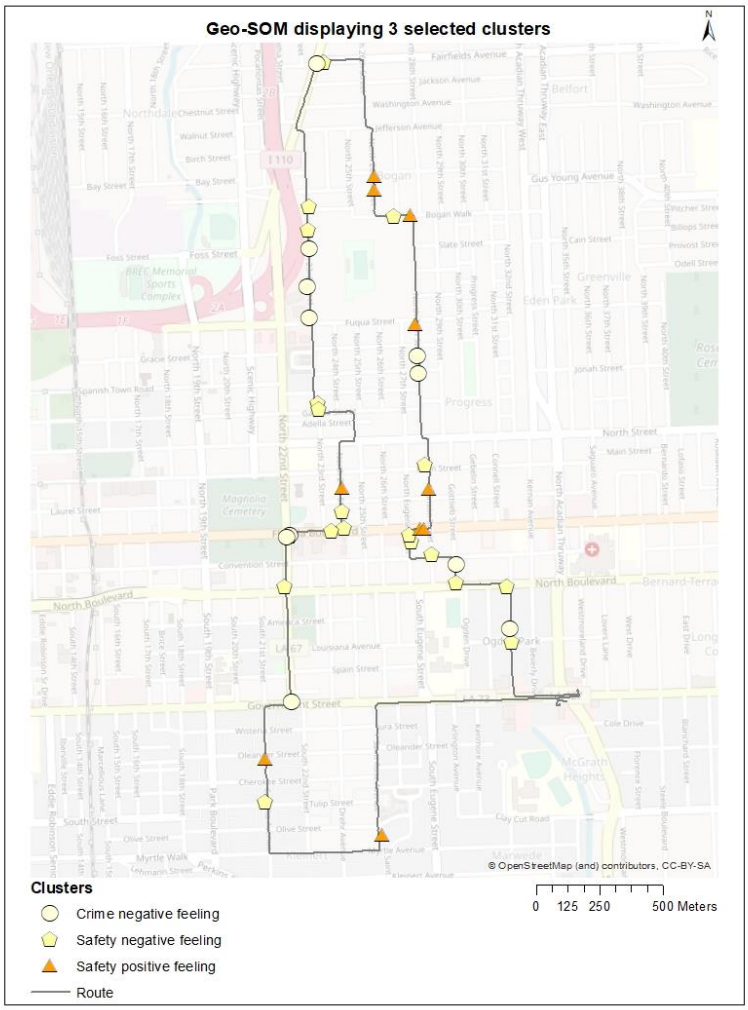


Figure 46. Example of a Geo-SOM visualization with statements made by a student

6.4.5 Skin-conductive wristbands

Figure 47 gives an output example of one of the participant's physiological measurements implemented during geo-narratives. Data includes Electrodermal Activity (blue line) also known as Galvanic Skin Response (GSR), Blood Volume Pulse (red line), Acceleration (purple line), Heart Rate (orange line), and Temperature (green line). Further analysis and interpretation of the physiological measurements will be carried out in future research.

Figure 47. Example of physiological measurements with skin-conductive wristbands

Chapter 7

7 Discussion

The purpose of this discussion section is to interpret the results in regard to the following three research questions:

I. How can innovative geospatial technologies, like spatial video and geo-narrative, be effectively used to identify physical urban blight types and to measure individual's perception of crime?
II. What kind of relationship exists between physical urban blight and crime in Baton Rouge?
III. What factors influence subjective perceptions of crime in Baton Rouge?

The second part of this chapter discusses benefits and limitations of the employed methodology.

7.1 Results interpretation

Results presented in this thesis show that urban blight is correlated with crime. All statistically significant results show a positive correlation. Homicides show a strong correlation with blocked windows. Battery and narcotics are highly correlated with different blight types, such as abandoned buildings, broken windows, blocked windows, unkempt areas etc. Battery shows additionally a strong relationship with building graffiti. Litter and structural integrity are strongly correlated with crime. The majority of correlation coefficients for burglary, vice, illegal parking and infrastructural graffiti are not statistically significant.

Remarkable is the division line between north and south in Baton Rouge. Results show clearly that the high blight and crime areas in Baton Rouge are located north of Government Street. Looking at the demographics, the northern area is considered the low-income area. Therefore, also low-income is related to blight and crime. Government Street crosses horizontally through the neighborhood Mid City. Within one neighborhood remarkable differences are visible. It can be distinctly stated that the neighborhood Fairfields and the northern part of the neighborhood Mid

City are the problem areas in the study area. Moreover, it could be noticed that in a more affluent neighborhood numerous blight indicator are present. In the meantime, in high blight areas well-kept houses and areas could be identified. By observing the high blight neighborhoods in detail, some positive changes were made. Thus, for example, a supermarket that contained a large amount of graffiti got painted during the time period of the survey and an area with new well-kept houses was built in the middle of a high blight area.

Moreover, it could be detected that violent crimes are more concentrated in the northern low-income areas, whereas non-violent crimes are more extended to the southern mid-class neighborhoods. An explanation for this pattern is that low income communities deal with social problems. Risk factors caused by poverty are for example a lack of health insurance, drug consumption, poor houses, gang formation, and homelessness. These factors are leading to violent crimes, such as assault and homicides. Non-violent crimes involve mostly property crime. The extension of non-violent crimes to the southern mid-class neighborhoods of Baton Rouge is linked to the higher value of houses, which is more attractive for burglars.

The relationship between urban blight, specifically broken windows, and crime is stated in the Broken Windows Theory. In regard to this case study the theory can be confirmed, which means that untended urban blight leads to crime. Supporting the Broken Windows Theory applying spatial video has not been researched before. Although, the relationship between physical urban blight and crime can clearly be identified, there are no indications that crime rates decrease if blight decreases or is even eliminated. Therefore, in future research, spatio-temporal analysis is essential to assess possible interventions by city stakeholders against blight.

Comparing the 311 reported blight data and the urban blight data collected with the spatial video, it can be noticed that the spatial video data collection is more precise, consistent, and flexible. 311 data do not make a distinction between different urban blight indicators. Indicators are joined in bigger sub-categories. Local stakeholders, who report the data have not a standardized way of assessing and reporting blight. By applying the proposed methodology, the assessment and analysis of blight are standardized and therefore comparisons can be made. Depending on the research interest, analysts can focus on either blight in general, property blight, environmental blight, or specific blight indicators. This makes it easier to find correlations with specific crime types and to identify hotspots of specific blight indicators. After identifying hotspot areas, stakeholders know

exactly where and on which type of urban blight they have to invest. Moreover, subjective perceptions of safety and crime during field work can be included to identify and map high fear areas. Eventually temporal analysis can be carried out to see if crime rates indeed decrease by eliminating urban blight.

Based on statements from geo-narrative participants, it can be noted that people feel less safe in areas with a high level of blight. People tend to feel safer, if they are familiar with a similar environment. The majority of participants thinks that abandoned buildings attract homeless people and drug trafficking and they perceive these areas as unsafe. Test subjects also stated frequently that the northern area is a low-income area with drug problems and gangs. Moreover, experts mentioned that the majority of illegal dumping is not caused by local residents, but by people who do not live in these neighborhoods. There is no explicit answer on the question, if people feel safer in residential or in commercial areas. However, the majority of the people answered to feel less safe during evenings and night and when they see people hanging around on streets. Some participants experience that the area around Government Street is gentrifying. Investments are made, houses are renovated, and property prices start to increase.

In order to assess urban blight data and its correlation with crime, it is important to consider also the cultural and historical background of communities that shape the identity of a neighborhood. Residents of these neighborhoods may have other priorities or perspectives on how a neighborhood should look like and may disregard the appearance of their property or environment. A community driven strategy has to be developed in order to reduce blight. It is important to engage with community leaders and residents in order to effectively eliminate blight in affected neighborhoods. In order to reduce crime also other factors have to be considered. Based on the results it can be noted that urban blight occurs most likely in areas where crime is concentrated, however, crime does not implicitly occur in urban blight areas. This statement indicates that urban blight is not the only trigger for crime.

7.2 Benefits and Limitations

A limitation of the employed spatial video technology is the camera's sensitivity to many different factors, depending on weather conditions, speed of travel, parked cars, and GPS connection.

Sunlight for example affects the recordings due to reflections, which makes especially the identification of broken windows difficult. Also, the shadows of big trees influence the quality of the recordings. Moreover, heavy precipitations limit the visibility for data extraction. Especially video recordings from side windows that are not equipped with wipers are affected by rain. Another issue is a faster driving speed, which makes the identification of close objects difficult as well as elements that obscure the view of buildings or parcels, specifically parked cars. Another issue of the spatial video technology is that data collection is limited to daytime. In this research, all streets within one neighborhood were covered. Closed streets impact the completeness of the data set. Other limitations of the spatial video system are the sensitivity of the GPS signal towards high buildings or dense vegetation. During the field work in Baton Rouge the GPS signal got lost several times. To avoid driving the same trajectory again, two additional cameras were mounted to the side windows of the vehicle. To ensure that data are saved properly, every 30 minutes a new recording was started.

Moreover, the digitization of urban blight from spatial videos faced some problems. In many cases, it was hard to differentiate between dumping and garbage that had to be picked up. Especially in Fairfields and Mid City many huge piles of garbage could be found next to garbage bins. If it seemed that piles were present for more than one week and had not been picked up, the location was digitized as “dumping”. The same applies for abandoned buildings. Some people use to live in properties that contain all indicators of abandonment. However, it is hard to identify if somebody really lives in the house, therefore every building that appeared abandoned is assigned to the category “abandoned property”.

Various errors occurred during data collection and extraction of information from the spatial video. The “Storyteller software” provided with the Contour +2 cameras showed errors. The map with its corresponding GPS track was not shown in the software. Therefore the “Video player software” developed by Andrew Curtis and his team is used for data extraction. Additionally, GPS tracks on the map showed sometimes errors, not representing the real track. The digitization process had to be carried out meter by meter looking at street signs of the video, without having the exact location on the map.

Additionally, the data collection with geo-narratives showed limitations. Background noises can impair the quality of audio recordings. Therefore, it is important to equip cameras additionally with

recording devices and to mount the device in proximity of the speaker to ensure a good audio quality. Another issue with the geo-narratives is that by directly asking participants about safety perception, the participant may be influenced, and they may be more fearful. It is also difficult to compare data across all participants, because only temporal specific data are collected. Participants can perceive an area differently depending on weather conditions or if people are hanging around on streets. In this case study, participants also perceived the neighborhood differently, because they were sitting in an enclosed and safe environment, the car. If they would have walked outside, they would have a different perception of safety.

As for the wristbands it is hard to interpret the collected data. It needs professional assessment of experts. The physiological measurements depend also on the age or health condition of participants, the heartbeat can go up because of other factors than the fear of crime.

In contrast, the employed geospatial technology also shows many benefits. The collected material and the analyzed data sets can serve as important historical archives for future research. The employed geospatial technology allows spatio-temporal analysis of environmental characteristics on a fine-scale level and enables a time-efficient, cost-effective, precise, and easy-to-use data acquisition method in contrast with traditional and state-of-the-art data collection methods, such as professional handheld data collectors, the systematic social observation method, Google Street View or self-report measures. In addition, the data acquisition is under control of the researcher and therefore more flexible to use.

Chapter 8

8 Conclusion

This study presented a new standardized methodological approach to collect, process, and model urban blight on a fine-scale level. The data collection with spatial video, geo-narratives and skin-conductive wristbands is a unique approach of combining visual, audio and physiological measurements which has never been carried out before at this level. The collected data sets can serve as an important historical document for future research.

In total, five neighborhoods with a very high, high, moderate, low, and very low crime density in Baton Rouge have been selected as the study area. In total, 384 km over an eight-day period were driven during the spatial video collection. After digitizing the physical urban blight indicators that are defined in the standardized criteria catalogue, a series of statistical methods, including spatial description, kernel density estimation, and Spearman's correlation were carried out. In order to compare different maps with each other, the same bandwidths and raster extents were chosen. A total of 1,717 urban blight locations were digitized, with each location containing multiple indicators. 69 % of all indicators fell under environmental/infrastructural blight and 31% fell under property blight indicators. Analysis results revealed that urban blight locations are strongly and positively correlated with crime locations. 49 % of blight locations are present in the highest crime areas, whereas only 2% of blight locations could be identified in the lowest crime area. It should be noted that social urban blight indicators have not been considered during this study.

Additionally, geo-narratives are applied as a methodological approach to study the subjective perception of place-based crime. In total, 46 interviews were conducted while driving in the car on a specific route that included high crime, medium crime, and low crime areas. Participants made comments during drives based on context specific experiences. Before analyzing the data, audio recordings had to be transcribed. Various text-mining methods were carried out, including clustering algorithms by means of Geo-SOMs and the creation of word clouds. In general, people tend to feel less safe in areas, where blight is concentrated and they perceive urban blight as a crime attractor. If people are familiar with the environment, they tend to feel safer in high crime areas. It

should be noted that due to time limitations not all geo-narrative data could be analyzed. Similarly, the analysis and interpretation of the data collected with wristbands were not included in this thesis.

Based on this case study the relationship between urban blight, crime, and the fear of crime, as hypothesized by the Broken Windows Theory could be supported. However, with the results from this analysis, it is not possible to determine whether crime rates decrease, if urban blight is eliminated.

Limitations of the employed methodology included unfavorable weather conditions or bad GPS signals. Moreover, the digitization process was time consuming. At the same time, the methodology showed many advantages over traditional methods. The data set collected in this study can be more flexibly applied, and it is more consistent and precise, than the already existing 311 data set. It is a cost-effective and time-efficient method that enables quantitative and qualitative field data collection of spatio-temporal environmental phenomena.

8.1 Future work

The applied technologies, including spatial video, geo-narratives, and skin-conductive wristbands, and the methodological approach of assessing urban blight have a wide potential for future research.

Future research can, for example, proceed by analyzing all geo-narrative transcripts and interpreting physiological measurements collected with the E4 Empatica wristbands. Human perceptions of crime can be assessed to enhance the spatial video data collection. Future analysis can be carried out by researchers working at the University of Salzburg, i.e. experts working on the "Urban Emotions project" who developed an algorithm to extract moments of stress and to interpret physiological measurements[11].

The next important future step would be to provide city officials and other stakeholders with important information regarding blight collection and modeling in order to understand the spatial patterns of blight in Baton Rouge. After identifying hotspots of blight, stakeholders can invest in

[11] Resch et al. https://giscience.zgis.at/urban-emotions/
Alina Ristea http://dk-giscience.zgis.net/index.php/58-students2015/298-alina-ristea

these areas and repeat the data collection in order to identify changes of blight and crime over time. Moreover, also subjective urban blight or other socio-demographic data could be collected in the future, in order to have a more comprehensive assessment of urban blight.

Another important aspect for future research is the possibility of data extraction applying machine learning algorithms that recognize images with blight indicators automatically. The data extraction could speed up transferring urban blight indicators from a video into a GIS environment in an automated way. The attribute table in the proposed data set is developed as a basis for automated image extraction, by including a column that contains images for each blight location. These data could be trained for automatic image recognition applying artificial intelligence. Additionally, the transformation from the geo-narrative audio recordings to text files has the potential to be further simplified and accelerated. Transcripts of geo-narratives could be easily automated with already existing text recognition methods.

If it is possible by law, the utilization of UAVs could be considered to broaden the field of view of video recordings. By collecting spatial video from the streets, the data collection is limited to a specific angle that does not capture entire objects. UAVs would allow a 360º data acquisition.

Another potential for future research is to include the newly extracted information (e.g., blight indicators) for crime prediction models or to carry out social media text analysis based on crime perception.

Built upon this study, temporal analysis could be carried out by monitoring changes of blight and crime over time. The proposed standardization of blight allows to track changes over time or to compare different areas within a city or across different cities or countries. Depending on the study area, the indicators in the criteria catalogue can be adjusted. Moreover, local laws have to be taken into consideration concerning the permission of collecting and processing public video material. The employed technology is not limited to urban blight studies but can be used in a wide field of environmental research, such as health studies and post-disaster management, to improve the quality of life in local areas.

9 Bibliography

Ananyan, S. (2004): Crime pattern analysis through text mining: AMCIS 2004 Proceedings. Available online at https://pdfs.semanticscholar.org/2fdf/5084b00c65051a018680c0d9f2327be01b71.pdf.

Anliu Jiang (2017): Crime analysis in the city of baton rouge and BREC park based on crime location quotient and hotspot method. Masterthesis. Louisiana State University, checked on 10/11/2018.

Anselin, L. (1995): Local Indicators of Spatial Association — LISA. In *Geographical Analysis* 27, pp. 93–155.

Anselin, L. et al. (2019): GeoDa. An Introduction to Spatial Data Analysis. Version 1.12: Anselin, L. et al.

ArcMap. ArcGIS Desktop. Version 10.6 (2018): ESRI. Available online at https://desktop.arcgis.com/de/arcmap/, checked on 1/3/2019.

Bação, Fernando; Lobo, Victor; Painho, Marco (2005): The self-organizing map, the Geo-SOM, and relevant variants for geosciences. In *Computers & Geosciences* 31 (2), pp. 155–163. DOI: 10.1016/j.cageo.2004.06.013.

Braga, Anthony A.; Welsh, Brandon C.; Schnell, Cory (2015): Can Policing Disorder Reduce Crime? A Systematic Review and Meta-analysis. In *Journal of Research in Crime and Delinquency* 52 (4), pp. 567–588. DOI: 10.1177/0022427815576576.

Chainey, Spencer; Ratcliffe, Jerry (2005): GIS and crime mapping. West Sussex, England: Wiley (Mastering GIS).

Chen, Peter Y.; Popovich, Paula M. (2006): Correlation. Parametric and nonparametric measures. [Nachdr.]. Thousands Oaks, Calif.: Sage Publ (Sage university papers Quantitative applications in the social sciences, 139).

Curtis, A.; Blackburn, J. K.; Smiley, S. L.; Yen, M.; Camilli, A.; Alam, M. T. et al. (2016): Mapping to Support Fine Scale Epidemiological Cholera Investigations: A Case Study of Spatial Video in Haiti. In *International journal of environmental research and public health* 13 (2).

Curtis, A.; Curtis, J. W.; Kennedy, S. W.; Kulkarni, A.; Auer, T. (2013a): A Methodology for Assessing Dynamic Fine Scale Built Environments and Crime: A Case Study of the Lower 9th Ward After Hurricane Katrina. In Michael Leitner (Ed.): Crime Modeling and Mapping Using Geospatial Technologies. Dordrecht: Springer (Geotechnologies and the Environment, 8), pp. 203–225.

Curtis, Andrew; Blackburn, Jason K.; Widmer, Jocelyn M.; Morris, J. Glenn (2013b): A ubiquitous method for street scale spatial data collection and analysis in challenging urban environments: mapping health risks using spatial video in Haiti. In *International journal of health geographics* 12, p. 21. DOI: 10.1186/1476-072X-12-21.

Curtis, Andrew; Curtis, Jacqueline W.; Shook, Eric; Smith, Steve; Jefferis, Eric; Porter, Lauren et al. (2015): Spatial video geonarratives and health: case studies in post-disaster recovery, crime, mosquito control and tuberculosis in the homeless. In *International journal of health geographics* 14, p. 22. DOI: 10.1186/s12942-015-0014-8.

Curtis, Jacqueline W.; Curtis, Andrew; Mapes, Jennifer; Szell, Andrea B.; Cinderich, Adam (2013c): Using Google Street View for systematic observation of the built environment: analysis of spatio-temporal instability of imagery dates. In *International journal of health geographics* 12, p. 53. DOI: 10.1186/1476-072X-12-53.

EBRGIS Open Data (2019): City of Baton Rouge and Parish of East Baton Rouge. East Baton Rouge GIS Map Portal. Available online at http://data-ebrgis.opendata.arcgis.com/.

Eck, J. E.; Chainey, S.; Cameron, J. G.; Leitner, M.; Wilson, R. E. (2005): Mapping Crime: Understanding Hot Spots. Edited by U.S. Department of Justice. National Institute of Justice. Washington.

Gau, Jacinta M.; Pratt, Travis C. (2010): Revisiting Broken Windows Theory: Examining the Sources of the Discriminant Validity of Perceived Disorder and Crime. In *Journal of Criminal Justice* 38 (4), pp. 758–766. DOI: 10.1016/j.jcrimjus.2010.05.002.

Hagenauer, J.; Helbich, M. (2016): SPAWNN: A Toolkit for SPatial Analysis With Self-Organizing Neural Networks. In *Transactions in GIS* 20 (5), pp. 755–775.

Hart, T. C.; Zandbergen, P. A. (2012): Effects of Data Quality on Predictive Hotspot Mapping. Final Technical Report. With assistance of National Institute of Justice.

Hinkle, Joshua C.; Weisburd, David (2008): The irony of broken windows policing: A micro-place study of the relationship between disorder, focused police crackdowns and fear of crime. In *Journal of Criminal Justice* 36 (6), pp. 503–512. DOI: 10.1016/j.jcrimjus.2008.09.010.

Hipp, J. R. (2007): Block, Tract, and Levels of Aggregation: Neighborhood Structure and Crime and Disorder as a Case in Point. In *American Sociological Review* 72 (5), pp. 659–680.

Hogg, Robert V.; Tanis, Elliot A. (2010): Probability and statistical inference. 8th ed. Upper Saddle River, NJ: Prentice Hall.

Kaplan, Jacob (2019): Uniform Crime Reporting Program Data: Offenses Known and Clearances by Arrest, 1960-2017.

Kelling, George L.; Wilson, James Q. (1982): Broken Windows. The police and neighborhood safety. In *Atlantic Monthly* 249 (3), pp. 29–38.

Kwan, M.; Ding, G. (2008): Geo-Narrative. Extending geographic information systems for narrative analysis in qualitative and mixed-method research. 4th ed. 60 volumes: The Professional Geographer, checked on 10/25/2018.

Levine, N. (2015): CrimeStat. A Spatial Statistics Program for the Analysis of Crime Incident Locations. Version v 4.02. Houston: Ned Levine & Associates; National Institute of Justice.

Longley, Paul; Goodchild, Michael F.; Maguire, David J.; Rhind, David William (2015): Geographic information science & systems. Fourth edition. Hoboken, N.J.: Wiley.

Maghelal, P.; Andrew, S. A.; Arlikatti, S.; Jang, H.S (2013): From blight to light. Assessing blight in the city of Dallas. Final Report. Department of Public Administration University of North Texas. Available online at https://www.dallasareahabitat.org/wp-content/uploads/2015/09/Blight-Study.pdf, checked on 10/12/2018.

Marco, Miriam; Gracia, Enrique; Martín-Fernández, Manuel; López-Quílez, Antonio (2017): Validation of a Google Street View-Based Neighborhood Disorder Observational Scale. In

Journal of Urban Health : Bulletin of the New York Academy of Medicine 94 (2), pp. 190–198. DOI: 10.1007/s11524-017-0134-5.

Mayring, Philipp (2010): Qualitative Inhaltsanalyse. Grundlagen und Techniken. 11.th ed. Weinheim, Basel: Beltz Verlag.

Mills, Jacqueline W.; Curtis, Andrew; Kennedy, Barrett; Kennedy, S. Wright; Edwards, Jay D. (2010): Geospatial video for field data collection. In *Applied Geography* 30 (4), pp. 533–547. DOI: 10.1016/j.apgeog.2010.03.008.

Moore, H. C. (2018): State of crime: 2018. A look at crime and response needs in East Baton Rouge Parish. With assistance of East Baton Rouge District Attorney's Office. East Baton Rouge District Attorney's Office, checked on 10/11/2018.

National Institute of Justice (2013): MAPS: How Mapping Helps Reduce Crime and Improve Public Safety. Nij. Available online at https://www.nij.gov/topics/technology/maps/Pages/reduce-crime.aspx, checked on 10/11/2018.

National Institute of Justice (2018): Mapping and Analysis for Public Safety. Nij. Available online at https://www.nij.gov/topics/technology/maps/pages/welcome.aspx, checked on 10/11/2018.

Open Data BR (2019): Open Data Baton Rouge. City of Baton Rouge. Available online at https://data.brla.gov/.

Openshaw, Stan (1984): The modifiable areal unit problem. Norwich: Geo Abstracts Univ. of East Anglia (Concepts and techniques in modern geography, no 38).

Oxford dictionaries (2019): Blight. Available online at https://en.oxforddictionaries.com/definition/blight.

Pasadena community development commission (2010): Report to the city council for the proposed merger of the northwest redevelopment projects, and the proposed amendment no. 4 to the Villa-parke redevelopment plan. Urban Futures Incorporated. Orange, California.

Ratcliffe, Jerry H. (2004): Geocoding crime and a first estimate of a minimum acceptable hit rate. In *International Journal of Geographical Information Science* 18 (1), pp. 61–72. DOI: 10.1080/13658810310001596076.

Riegl, B.; Korruble, J.; Martin, C. (2001): Mapping and monitoring of coral communities and their spatial patterns using a surface-based video method from a vessel. In *Bulletin of Marine Science* 69 (2), pp. 869–880.

Ross, Catherine E.; Mirowsky, John (2001): Neighborhood Disadvantage, Disorder, and Health. In *Journal of Health and Social Behavior* 42 (3), p. 258. DOI: 10.2307/3090214.

Sampson, Robert J.; Raudenbush, Stephen W. (1999): Systematic Social Observation of Public Spaces: A New Look at Disorder in Urban Neighborhoods. In *American Journal of Sociology* 105 (3), pp. 603–651. DOI: 10.1086/210356.

Sampson, Robert J.; Raudenbush, Stephen W. (2001): Disorder in Urban Neighborhoods - Does It Lead to Crime? National Institute of Justice. Available online at https://www.ncjrs.gov/pdffiles1/nij/186049.pdf.

Skogan, W. G. (2008): Broken windows: Why and how we should take them seriously. In *Criminology & Public Policy* 7 (2), pp. 195–201.

Skogan, W. G. (2012): Disorder and Crime. In Brandon Welsh, David P. Farrington (Eds.): The Oxford handbook of crime prevention. New York, NY: Oxford University Press (Oxford handbooks in criminology and criminal justice), pp. 173–188.

Skogan, Wesley G. (1990): Disorder and decline. Crime and the spiral of decay in American neighborhoods. New York: Free Press (52).

Smith, S. C.; Bruce, C. W. (2008): CrimeStat III. User Workbook. The National Institute of Justice. Washington.

Strelnikova, Dariia; Schneider, Thomas; Leitner, Michael (2018): Utilizing Spatial Video to Analyse Roadside Advertisements in Villach, Austria. In *giforum* 1, pp. 34–46. DOI: 10.1553/giscience2018_01_s34.

Tobler, W. R. (1970): A Computer Movie Simulating Urban Growth in the Detroit Region. In *Economic Geography* 46, p. 234. DOI: 10.2307/143141.

United States Census Bureau (2011): Unit of Analysis. Available online at https://www.census.gov/hhes/www/housing/housing_patterns/unitofanalysis.html.

United States Census Bureau (2018a): Household Income: 2017. With assistance of Gloria G. Guzman. Available online at https://www.census.gov/content/dam/Census/library/publications/2018/acs/acsbr17-01.pdf.

United States Census Bureau (2018b): QuickFacts. Baton Rouge city, Louisiana. Available online at https://www.census.gov/quickfacts/batonrougecitylouisiana, checked on 10/11/2018.

Valasik, Matthew; Brault, Elizabeth E.; Martinez, Stephen M. (2018): Forecasting homicide in the red stick: Risk terrain modeling and the spatial influence of urban blight on lethal violence in Baton Rouge, Louisiana. In *Social Science Research*. DOI: 10.1016/j.ssresearch.2018.12.023.

van Bakergem, Margaret; Sommer, Evan C.; Heerman, William J.; Hipp, James Aaron; Barkin, Shari L. (2017): Objective reports versus subjective perceptions of crime and their relationships to accelerometer-measured physical activity in Hispanic caretaker-child dyads 95 Suppl, S68-S74. DOI: 10.1016/j.ypmed.2016.12.001.

van der Weele, Joël J.; Flynn, Mataka P.; van der Wolk, Rogier J. (2017): Broken Window Effect. In Alain Marciano, Giovanni Battista Ramello (Eds.): Encyclopedia of Law and Economics, vol. 37. New York, NY: Springer New York, pp. 1–4.

Weisburd, D.; Hinkle, J. C.; Famega, C.; Ready, J. (2010): Legitimacy, Fear and Collective Efficacy in Crime Hot Spots: Assessing the Impacts of Broken Windows Policing Strategies on Citizen Attitudes. U.S. Department of Justice.

Wilson, R. E. (2005): Conclusion. In U.S. Department of Justice (Ed.): Mapping Crime: Understanding Hot Spots. National Institute of Justice. Washington, pp. 65–71.

Appendix A. Background questionnaire

Background questionnaire - Safety Perception in the city of Baton Rouge

Thank you for participating in our research about **safety perception**. The research focuses on the perception of crime in Baton Rouge and on assessing urban blight and its relationship with criminal activities.

Your contribution is highly appreciated and your answers will be kept strictly confidential.

This survey consists of two parts, (1) filling out a brief questionnaire and (2) a short mapping exercise.

Thank you for taking part and helping out with our research. We really appreciate your time and effort! Please, answer ALL questions! There are no right or wrong answers, all responses are truly helpful to us.

It takes about 3-5 minutes to complete this survey.

1) Assessment Background Questionnaire

Please answer the following questions:

a) Residence Information

Currently living in Baton Rouge? ☐ yes ☐ no

If yes, please mention where you live: Click or tap here to enter text. (please provide your residential address or your neighborhood information)

If yes, since when have you lived in Baton Rouge? Click or tap here to enter text.

How do you generally travel within the city of Baton Rouge? (please check more than one box, if needed)

☐ bus
☐ car
☐ bike
☐ walk
☐ other: Click or tap here to enter text.

b) Safety Perception

How safe do you feel in Baton Rouge, in general?

☐ very safe

☐ safe

☐ moderate

☐ unsafe

☐ very unsafe

Where do you feel less safer in the city? (please check more than one box, if needed)

☐ Public parks or greens
☐ Sidewalks
☐ Convenience stores
☐ Cabs
☐ Buses
☐ Gas stations
☐ Construction zones
☐ Under bridges or underpasses
☐ Alleys
☐ Other: Click or tap here to enter text.

Score the elements that influence your perception of crime from the list below from 1 (influences me not at all) to 5 (influences me most).

Click or tap here to enter text. Social media info

Click or tap here to enter text. Family and friends' opinions

Click or tap here to enter text. Bad experiences in the city

Click or tap here to enter text. Types of people living in the city

Click or tap here to enter text. Crime hot spots

Click or tap here to enter text. Other: Click or tap here to enter text.

When do you feel unsafe? (please check more than one box, if needed)

☐ morning (7 am to 12 noon)

☐ afternoon (12 noon to 5 pm)

☐ evening (5 pm to 8 pm)

☐ night (8 pm to 7 am)

☐ never

Why do you think Baton Rouge is dangerous? (please check more than one box, if needed)

☐ It is a poor area.

☐ My family and friends think it is dangerous and they influence me.

☐ I am familiar with crime data and know the crime statistics.

☐ It has a lot of homeless people.

☐ People who live in Baton Rouge say it is dangerous.

☐ I had some bad experiences in the city.

☐ The ethnicity of the people living in the city.

☐ Other: Click or tap here to enter text.

Are there specific places (public or private ones) you avoid due to safety concerns? ☐ yes ☐ no

If yes, please specify these places: Click or tap here to enter text.

Have you been a victim of a crime in Baton Rouge? ☐ yes ☐ no

If yes, please specify in more detail: Click or tap here to enter text.

How does **urban blight** influence your perception of safety?
(**Urban blight** describes disordered neighborhoods characterized by abandoned buildings, broken windows, high-grown vegetation etc.)

☐ a lot – I feel much less safe in these areas

☐ medium – I feel less safe in these areas

☐ low – I almost feel the same way as in areas with little to no urban blight

☐ not at all – I don't feel any difference compared to areas with little to now urban blight

c) City and neighborhood

Enter your perceived score from 1 to 5 for each one of the following attributes for the **entire city** of Baton Rouge, where 1 means "not at all" and 5 means "completely":

The city is safe	☐1	☐ 2	☐ 3	☐ 4	☐5
The city is wealthy	☐1	☐ 2	☐ 3	☐ 4	☐5
The city is beautiful	☐1	☐ 2	☐ 3	☐ 4	☐5
The city is boring	☐1	☐ 2	☐ 3	☐ 4	☐5
The city is livable	☐1	☐ 2	☐ 3	☐ 4	☐5
The city is walkable	☐1	☐ 2	☐ 3	☐ 4	☐5
The city is cycling friendly	☐1	☐ 2	☐ 3	☐ 4	☐5
The city has good public transport	☐1	☐ 2	☐ 3	☐ 4	☐5
The city is depressing	☐1	☐ 2	☐ 3	☐ 4	☐5

Enter your perceived score from 1 to 5 to each one of the following attributes for **your neighborhood/residential address** of Baton Rouge, where 1 means "not at all" and 5 means "completely":

My neighborhood is safe	☐1	☐ 2	☐ 3	☐ 4	☐5
My neighborhood is wealthy	☐1	☐ 2	☐ 3	☐ 4	☐5
My neighborhood is beautiful	☐1	☐ 2	☐ 3	☐ 4	☐5
My neighborhood is boring	☐1	☐ 2	☐ 3	☐ 4	☐5

My neighborhood is livable	☐1	☐ 2	☐ 3	☐ 4	☐5
My neighborhood is walkable	☐1	☐ 2	☐ 3	☐ 4	☐5
My neighborhood is cycling friendly	☐1	☐ 2	☐ 3	☐ 4	☐5
My neighborhood has good public transport	☐1	☐ 2	☐ 3	☐ 4	☐5
My neighborhood is depressing	☐1	☐ 2	☐ 3	☐ 4	☐5

d) General Information

Gender: ☐ male ☐ female

Age: Click or tap here to enter text. years

Nationality: ☐ US citizen ☐ non-US citizen

Student: ☐ yes ☐ no

If no, what is your profession? Click or tap here to enter text.

Save the document to your computer and send to: Judith.Stratmann@edu.fh-kaernten.ac.at

Appendix B. Photographs of blight indicators

The following photographs are samples of urban blight indicators in the criteria catalogue in Section 3.2. Images represent the level of blight (low, medium, high) that were observed during the field work in Baton Rouge in March 2019. It should be noted, that some photographs show more blight indicators.

PROPERTY BLIGHT

1) **Abandoned property**

   a) Low level.

   b) Medium level.

   c) High level.

2) **Broken window/door**

a) Low level.

b) Medium level.

c) High level

3) Blocked window/door

a) Low level

b) Medium level

c) High level.

4) No window/door

a) Low level

b) Medium level.

c) High level.

5) **Building graffiti**

a) Low level

b) Medium level

c) High level.

6) Structural integrity

a) Low level.

b) Medium level.

c) High level.

7) **Building overgrowth**

a) Low level.

b) Medium level.

c) High level.

8) Other

Car driven through facade

ENVIRONMENTAL / INFRASTRUCTURAL BLIGHT

1) **Overgrown vegetation**

   a) Low level.

   b) Medium level.

   c) High level

2) Litter

a) Low level.

b) Medium level.

c) High level.

3) Dumping

a) Low level.

b) Medium level.

c) High level.

4) Unkempt areas

a) Low level.

b) Medium level.

c) High level.

5) Illegal parking

a) Low level.

b) Medium level.

c) High level.

6) Abandoned vehicle

a) Low level.

b) Medium level.

c) High level.

7) **Infrastructural graffiti**

a) Low level.

b) Medium level.

c) High level: does not exist.

8) **Other:** Abandoned graveyard