Journal of Transport Geography 52 (2016) 38–50

Contents lists available at ScienceDirect

Journal of Transport Geography

journal homepage: www.elsevier.com/locate/jtrangeo

Spatial patterns and temporal dynamics of urban bicycle crashes—A case study from Salzburg (Austria)

Martin Loidl *, Christoph Traun, Gudrun Wallentin

Department of Geoinformatics, University of Salzburg, Hellbrunnerstraße 34, 5020 Salzburg, (Austria)

ARTICLE INFO

Article history:
Received 21 September 2015
Received in revised form 8 December 2015
Accepted 26 February 2016
Available online xxxx

Keywords:
Bicycle crashes
Exploratory analysis
Spatial and temporal dynamics

ABSTRACT

Most bicycle crash analyses are designed as explanatory studies. They aim to identify contributing risk factors and calculate risk rates based on – most of the time – highly aggregated statistical data. In contrast to such explanatory study designs, the presented study follows an exploratory approach, focusing on the absolute number of crashes. The aim is to reveal and describe patterns and dynamics of urban bicycle crashes on various spatial scale levels and temporal resolutions through a multi-stage workflow. Spatial units are delineated in the network space and serve as initial units of aggregation. In order to facilitate comparisons among regions and quantify temporal dynamics, a reference value of crash frequency is simulated for each unit of the respective spatial scale level and temporal resolution.

For the presented case study, over 3000 geo-coded bicycle crashes in the city of Salzburg (Austria) were analyzed. The data set covers 10 years and comprises all bicycle crashes reported by the police. Distinct spatial and temporal patterns with clusters, seasonal variations, and regional particularities could be revealed. These insights are indicators for urban dynamics in the transport system and allow for further, targeted in-depth analyses and subsequent counter measures. Moreover, the results prove the applicability of the proposed multi-stage workflow and demonstrate the added value of analyses of small aggregates on various scale levels, down to single crashes, and temporal resolutions.

1. Introduction

Cycling as an active mode of transport is healthy (Götschi et al., 2015; Holm et al., 2012) but dangerous relative to the distance traveled (Beck et al., 2007). Compared to driving a car, the risk for becoming involved in a crash is between 5.5 (ITF, 2012) and 12 (Delmelle and Thill, 2008) times higher for bicyclists—depending on the country and environment. Thus, it is not surprising that safety concerns are among the main reasons for rejecting the bicycle as a utilitarian mode of transport (Sanders, 2015; Winters et al., 2011). Generally, there is a broad consensus on the fact that road safety is one of the key factors for an increasing share of cyclists (Heinen et al., 2010; Thomas and DeRobertis, 2013; WHO, 2013). In order to face the safety issue, authorities, planners, and researchers have put much effort into building and improving bicycle infrastructure (Pucher et al., 2010; Rietveld and Daniel, 2004) and providing information about safe routes (Loidl and Zagel, 2014).

It is thus of crucial importance to better understand the patterns of crashes in terms of their spatial (where?) and temporal (when?) occurrence on a city-scale level. This degree of detail allows for further, targeted in-depth analyses and subsequent countermeasures. Although the prevalent safety concerns are widely acknowledged, crashes are rarely investigated on multiple temporal intervals and spatial scale levels, ranging from the city-scale to single crash locations. Many studies on bicycle crashes follow an epidemiological approach. This means that aggregated crash data are related to aggregated statistics which serve as exposure variables, such as annual travel distance. This way, an average risk exposure can be calculated for spatial reference units of different scales. Vandenbulcke et al. (2009) and Yiannakoulias et al. (2012) provide examples for risk calculations on a regional level, while Beck et al. (2007) performed risk calculations on a national level. A complementary approach relies on systematic in-depth analysis of individual crash samples to draw general conclusions on causalities, e.g. concerning bicycle facilities, road design, environmental conditions, and socio-demographic variables (e.g. Chen and Fuller, 2014; Harris et al., 2013; Lovelace et al., 2015; Teschke et al., 2012). Both approaches allow for a better understanding of certain aspects of bicycle safety, especially of contributing risk factors. Nevertheless, at least two issues still remain: First, the calculation of the risk exposure is often based on weak (in terms of spatial and temporal resolution, scale and accuracy) data, as extensively noted in the latest OECD report on bicycle safety (OECD, 2013). Additionally, large aggregates don't account for the dynamics within the reference units. Second, although crashes are rarely random but tend to be spatially dependent within a certain

* Corresponding author.
E-mail addresses: martin.loidl@sbg.ac.at (M. Loidl), christoph.traun@sbg.ac.at (C. Traun), gudrun.wallentin@sbg.ac.at (G. Wallentin).

http://dx.doi.org/10.1016/j.jtrangeo.2016.02.008
0966-6923/

area (Anderson, 2009; Xie and Yan, 2013), the spatial and temporal context of the data is mostly not considered explicitly in crash data analysis (Vandenbulcke-Plasschaert, 2011). With the approach proposed in this paper, we reveal the patterns of crash occurrences on multiple spatial scale levels and temporal resolutions. For this, we make use of the spatial and temporal information attached to the crash reports and establish a multi-stage workflow for a seamless, interactive exploration of the crash data.

2. Spatial and temporal analysis of bicycle crashes: Background and objectives

The body of scientific literature on bicycle safety has been growing constantly over the last two decades (Gerike and Parkin, 2015). Since the topic is tackled from various domain-specific and methodological perspectives, the intention here is to give a brief overview of a few major research avenues that are each further illuminated in the referenced literature.

A large number of studies deals with the relation of bicycle crashes and the physical environment (De Rome et al., 2013; Dozza and Werneke, 2014; Harris et al., 2013; Lusk et al., 2011; Reynolds et al., 2009; Teschke et al., 2012; Thomas and DeRobertis, 2013). Teschke et al. (2012) identified physical route characteristics that contribute to the risk of being involved in a crash. Lusk et al. (2011) compared the risk of on-road cycling to cycle tracks. While the focus of many risk estimations lies on the road segment, Harris et al. (2013) investigated risk factors at intersections. Both studies suggest that the separation of cyclists from motor vehicles and a low traffic speed increase the overall safety for bicyclists. Studies focusing on the spatial distribution of risk highlight the spatial variability of crash occurrences in terms of geography, type of environment or road class. Obvious spatial variabilities can be detected on a national scale, with the "bikeability" of the environment and bicycle safety politics as major explanatory variables (Vandenbulcke et al., 2009). De Geus et al. (2012) found that the majority of crashes occurred in built-up areas, when cyclists were driving on the main lane. De Rome et al. (2013) revealed a relatively high risk for being involved in a bicycle crash cycling on road and on shared paths for a study site in Australia. Although there is evidence for gender-specific cycling behaviors (Beecham and Wood, 2013; Garrard et al., 2008), the gender-specific risk tends to be insignificant according to several studies (e.g. De Geus et al., 2012; De Rome et al., 2013). Nevertheless, Martínez-Ruiz et al. (2015) found higher death rates for male cyclists. Lovelace et al. (2015) were not able to estimate the gender-specific risk but point to the fact, that the ratio of crashes involving female and male bicyclists was 1:8. Concerning the age, Kröyer (2015) found that the fatality risk increases with the age of the bicyclist who is involved in a bicycle–motorized vehicle crash. This is in line with findings by Degraeuwe et al. (2015).

Less research has been done so far on the temporal variability of bicycle crashes and the influence of seasonal dynamics, mainly associated with weather and road conditions. Doherty and Aultmann-Hall (2000) investigated the temporal variability of bicycle crash occurrences (not risk) and found significant differences between seasons but also between different urban environments. Aldred and Crosweller (2015) reconstructed incidents (crashes and near-misses) from travel diaries and correlated these events with the total travel time, binned to hours of a day. Their result shows distinct temporal patterns over the course of a day with peaks in the morning and evening rush hour. These findings are in line with Lovelace et al. (2015). Wanvik (2009) and Chen and Fuller (2014) linked road and light conditions with crash risk and found evidence for a larger prevalence of bicycle crashes in the darkness and in case of wet and icy road surfaces.

From a methodological perspective, the general study design, the level of aggregation and scale, the definition of adequate spatial references and existing approaches in point pattern analysis, both in space and time, are relevant.

Independent from the variable that is tested for, explanatory study designs (Lord and Mannering, 2010) require an exposure variable (typically distance traveled or number of trips). The type of exposure variable and the quality of the data directly impact the explanatory power of the results (OECD, 2013; Schepers, 2013). For bicycle-related investigations of risk patterns, sound exposure variables are hardly ever available, especially on a micro-scale. Unlike to explanatory approaches, exploratory analyses focus on the absolute number of incidents (crash frequencies instead of rates) and their respective spatial and/or temporal distribution as well as on their characteristics (Dai, 2012). Exploratory approaches do not necessarily require any exposure variables. In turn, they don't allow for definite conclusions on underlying processes. Instead, they serve as hypothesis generator and initial point for further explanatory investigations. As explanatory analyses are very data intensive, a preceding exploratory analysis that identifies potential causalities, associated with specific locations and time intervals, contributes to cut down the amount of required data considerably. This aspect is even more important when bicycle crash locations are investigated on a single-crash level where adequate exposure variables are hardly ever available for the particular location and point of time.

As mentioned in the introduction, many bicycle crash analyses follow an epidemiological approach where crash occurrences are related to spatially aggregated, statistical variables. Typically, the prevalence of crashes or the estimated risk are investigated on the level of administrative or statistical units, such as countries, states, municipalities, census districts, or regular grids (Anderson, 2009; Beck et al., 2007; Delmelle and Thill, 2008; Lovelace et al., 2015; Vandenbulcke et al., 2014). For spatial dynamics of bicycle crashes or risk exposure, especially on a micro-scale, one has to consider the potentially high variation within reference units (census districts tend to be too large) and furthermore account for the network-bound character of bicycle crashes. Thus, the Euclidean distance is inappropriate for the delineation of reference units and needs to be substituted by network-based alternatives (Okabe and Sugihara, 2012). As alternative to planar reference units for the analysis of bicycle crashes, several authors exclusively focus on junctions or segments respectively (Vandenbulcke-Plasschaert, 2011), while others slice the road network into equally long segments and use them as reference units. For the latter method, no matter which algorithm is applied, it has to be noted that fragments in peripheral areas always remain when the network is decomposed (Shiode, 2008). Roughly generalized, the delineation of reference units in networks can be approached from two sides. First, spatial, temporal, or spatio-temporal cluster detection algorithms can be applied in order to define regions that are similar in terms of crash occurrence or risk exposure (Eckley and Curtin, 2013; Shiode and Shiode, 2013; Steenberghen et al., 2010). Results of such data-driven approaches are hard to compare over several time intervals, due the variability of the spatial configuration. Second, spatial reference units are predefined, either using existing administrative units or applying delineation methods such as the quadrat method (Shiode, 2008) or Voronoi diagrams (Okabe and Sugihara, 2012). For the multi-stage workflow described in this paper, the latter approach was applied. This makes it easier to compare regions over time and reveal temporal dynamics. On the other hand, the MAUP (Wong, 2009) potentially remains an issue which needs to be taken into account when the results are interpreted.

As soon as bicycle crashes are investigated on a single crash level, a large variety of well-established methods and tools from many domains can be applied (Cressie, 1993; Diggle, 2013). In the context of crash analysis, the detection and characterization of black-spots or black-zones (clusters), the determination of significance, the degree of spatial dependency, and the variability over time are among the most eminent concerns. However, it needs to be considered that the majority of available algorithms were originally designed for the planar space. Thus, an adaption for the network space is required (Okabe and Sugihara, 2012). This leads to more reliable results, for example, in