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SPATIAL INFORMATION AND BICYCLING SAFETY

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Abstract: The bicycle is currently experiencing an impressive revival as sustainable transport mode. Numerous bicycle promotion initiatives have contributed to a significant increase of the bicycle's modal share during the past years. Nevertheless, safety concerns are among the most relevant factors that keep people from using the bicycle for their utilitarian trips.

Mobility – and in consequence bicycling safety – is spatial by its very nature. Thus, introducing the spatial perspective into bicycling promotion and safety research bears great potential with regard to spatial models, simulation and analysis. This review paper provides an overview of current research at the intersection of spatial information and bicycling safety and discusses the respective contributions in a broader context from literature.

Keywords: Bicycling, safety, GIS, spatial information

RÄUMLICHE INFORMATION ZUR ERHÖHUNG DER RADVERKEHRSSICHERHEIT

Zusammenfassung: Das Fahrrad erlebt aktuell eine bemerkenswerte Renaissance als nachhaltiges Verkehrsmittel. Bedingt durch zahlreiche Initiativen zur Radverkehrsförderung ist der Anteil des Radverkehrs in den meisten europäischen Städten während der letzten Jahre gestiegen. Allerdings verhindern Sicherheitsbedenken mitunter eine weitere Steigerung der Beliebtheit des Fahrrads als Alltagsverkehrsmittel.

Mobilität – und damit auch die Radverkehrssicherheit – ist räumlich. Folglich birgt die Verbindung von räumlicher Information und Radverkehrsförderung bzw. Forschung im Bereich der Radverkehrssicherheit ein großes Potenzial. Dieser Beitrag bietet einen Überblick über aktuelle Forschungsarbeiten an der Schnittstelle von räumlicher Information und Radverkehrssicherheit. Die jeweiligen Beiträge der räumlichen Perspektive werden vor dem Hintergrund eines breiten Literaturbefunds diskutiert.

Schlüsselwörter: Fahrradmobilität, Sicherheit, GIS, räumliche Information

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1 BICYCLING AND SAFETY

Bicycling is currently experiencing an impressive revival as sustainable mobility option for a number of good reasons, especially in urban environments. It is environmentally friendly (Lindsay et al. 2011, Johansson et al. 2017), healthy (Götschi et al. 2015), socially equitable (Pucher & Buehler 2008) and economically beneficial, both for individuals as well as for society (Fishman et al. 2015, Gilderbloom et al. 2016, Brey et al. 2017). Because of these advantages and increasingly negative impacts of car-centered policies and transport systems, governments around the world have been starting to heavily invest into bicycling promotion (Handy et al. 2014, Winters et al. 2017), with northwestern European countries as role models (Pucher & Buehler 2008).

Although many cities and regions are very successful in promoting bicycling and are witnessing an increase of the bicycle's modal share, substantial barriers for a further increase still exist. Among them, safety concerns are regarded as being the most prevalent. Winters et al. (2011) identified safety aspects as most influential deterrent for bicyclists in Vancouver. In another study, Winters et al. (2012) found that perceived safety corresponds well with the de facto levels of safety, with minor discrepancies between perceived and observed safety of bicycle tracks (perceived as less save as they actually were). Findings on the deterring influence of safety concerns are further disaggregated by Sanders (2015), who

found that the willingness to choose the bicycle is negatively impacted by perceived safety risk factors. However, this influence decreases with higher bicycling frequency. On the other hand, the awareness for safety threats increases with experience, mainly due to near miss events. Additionally, Beecham & Wood (2013) point to remarkable gender-differences in risk mitigation strategies: female bicyclists prefer quiet roads and parks on their routes much more than male bicyclists. Werneke et al. (2015) complement findings from surveys and crash data analysis by investigating safety-critical events in a naturalistic cycling study. They found that other road users were involved in the majority of safety-critical events. Around 20% of the events could be traced back to inadequate infrastructure. Nevertheless, infrastructure is crucially important, especially for children. Zhou et al. (2010) conducted a study among elementary and middle schools in Florida and found safety and security concerns as primary reason for the low share of school children bicycling to school. Emond & Handy (2012) on the other hand, concluded that for a city with a dense network of adequate bicycle infrastructure, such as Davis, CA, the main mode choice factor for pupils is the perceived distance to school. In any case, adequate and safe infrastructure is the backbone of any successful bicycling promotion activity. There is clear evidence for the relation of environmental factors, commonly summarized as "bikeability" and levels of bicycling (Ma &

Dill 2016, Sallis et al. 2016, Winters et al. 2016).

The number of fatalities in road traffic has been sharply decreasing since the 1970s all over Europe (Bergel-Hayat & Zukowska 2015). However, the decrease is less significant for bicyclists and even countertrends are observable in the EU (increase of bicyclist fatalities between 2013 and 2014), according to latest EU statistics (European Commission 2016). The share of bicyclists among all fatalities is still comparatively high, with large regional variabilities. The rise of the bicycle as utilitarian mode is regarded as one contributing factor to the slower decrease of fatalities of bicyclists (Evgenikos et al. 2016), although this contrasts the "Safety-in-numbers" effect, on which a broad consensus does exist in literature (Elvik & Bjørnskau 2017). Contrary to EU-wide developments, the Netherlands were successful in considerably reducing the number of bicycle crashes with a mix of measures, which address infrastructure, road users and vehicles (Schepers et al. 2017).

Putting together the three arguments so far – namely the potential of the bicycle as utilitarian mobility option, safety concerns as barrier for further bicycle usage and the relatively slow decrease of crashes and fatalities among bicyclists – makes the need for comprehensive actions evident. However, until recently bicycling safety has been researched within very different domains, ranging from trauma medicine to engineering, planning, bio-mechanics, law and
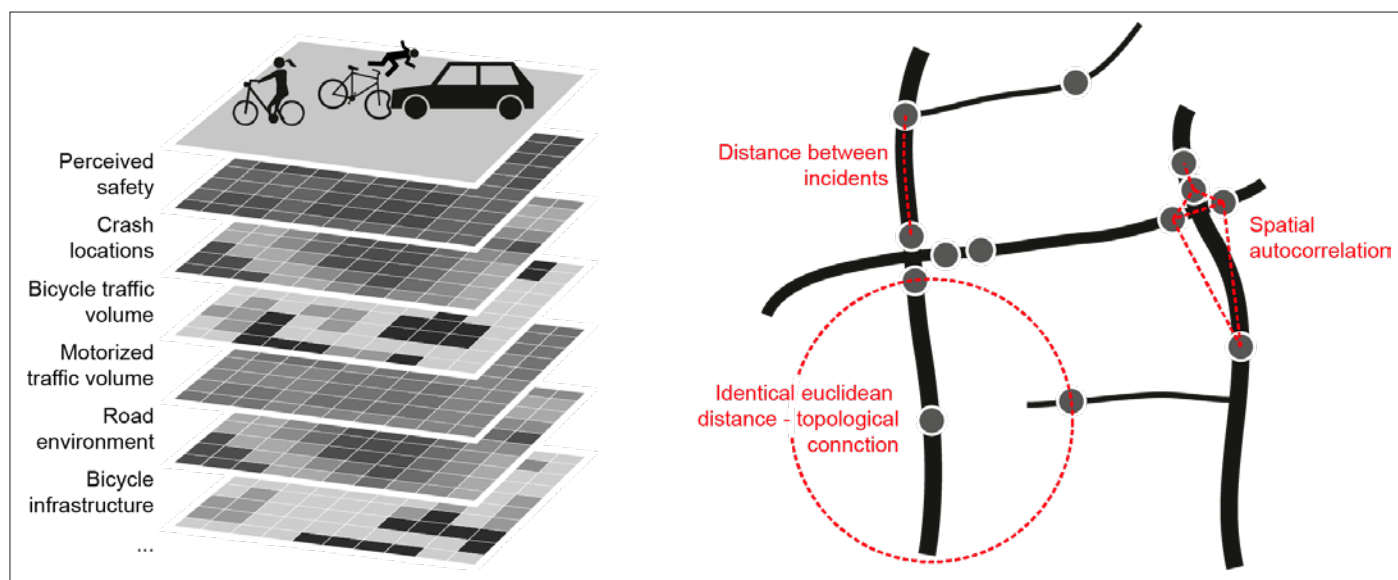

Figure 1: Spatial facets of bicycling safety (left) and relevant geographical concepts for crash analysis (right)
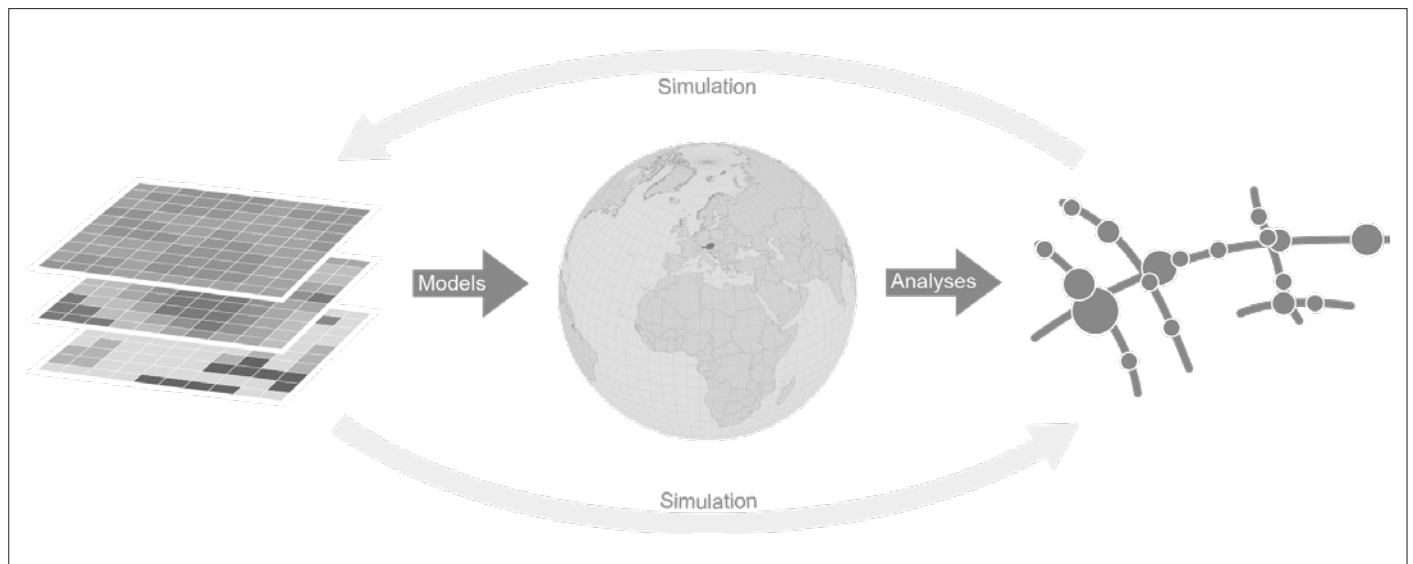
Figure 2: Spatial models represent real-world bicycle safety. Spatial analyses relate real-world phenomena and events to each other and put them into a spatial context. Spatial simulations are commonly built upon spatial models, while employing spatial analysis routines.

psychology, only to name a few. In order to overcome these "island solutions" and account for the complexity of bicycling safety we argue for integrated, multi-disciplinary approaches for promoting safe bicycling. As it will be shown in the remainder of this paper, geographical information systems have the capability to relate various perspectives on bicycling safety to each other, using the geographical space as common reference. Moreover, an explicitly spatial approach addresses the fundamental spatial characteristics of bicycling safety, which are often neglected in domain-specific solutions.

The contribution of the spatial perspective to bicycling safety research is the main subject in the following section. Then, the potential of spatial models, analyses and simulations is demonstrated with reference to previous and current studies by the author, before the main arguments are reflected and future research paths are illuminated in a concluding section.

2 THE SPATIAL PERSPECTIVE

Mobility is spatial by its very nature. It can be defined as movement of people or goods in space. Being mobile on a bicycle means to ride the bicycle from one location to another. Accordingly, bicycling safety becomes manifest in geographical space. Spatial facets of bicycling safety – from the suitability of the physical environment to the location of individually perceived safety threats – can be modeled and analyzed in

the spatial dimension (Figure 1, left). However, most studies on bicycling safety neglect location as a co-determining attribute of safety. Especially in the case of bicycle crash analyses, fundamental geographical concepts, such as proximity, spatial autocorrelation and topology (Figure 1, right), are hardly ever considered (Vandenbulcke-Plasschaert 2011).

Apart from the consideration of the fundamental spatial characteristics of bicycling safety and bicycle crashes in particular, an explicitly spatial perspective also facilitates integrated approaches for the mitigation of bicycling safety risks. Bicycle safety is a comparatively complex phenomenon that can be approached from several perspectives. They can be roughly divided into three categories: environment, vehicle and user. The environment, such as infrastructure (Teschke et al. 2012) or lighting conditions (Wanvik 2009), and the user's perception of it (Sanders 2015) can be related to locations and thus be modelled in a geographical information system (GIS). Using the geographical space as common reference, multiple perspectives on the road space can be related to each other in order to account for the multi-facetted complexity of bicycling safety (Loidl 2016).

Introducing the spatial perspective into bicycling safety research can be done from three angles: spatial models, spatial analysis and spatial simulation. Spatial models aim to identify influential factors and relate them to each other in a geographical con-

text in order to gain an adequate representation of real-world bicycling safety. However, it is important to be aware that models represent reality always in an abstract and generalized way (Nyerges 1991, Goodchild 1992). Spatial simulations are usually built upon spatial models and allow for "what-if" investigations (Batty & Torrens 2005) and the development of future scenarios. Spatial analyses gain additional insights through relating real-world phenomena or events to their respective spatial context. In the following section, all three spatial approaches to bicycling safety are further elaborated.

3 INTRODUCING THE SPATIAL PERSPECTIVE

This section provides an overview of how the three, aforementioned spatial approaches have been introduced into bicycling safety research. For this, I will primarily refer to previously published studies and ongoing research. Each of the examples is then discussed in the context of existing literature.

3.1 SPATIAL MODELLING

Spatial models are suitable to link different factors that contribute to the complexity of bicycling safety to each other. A model-based approach leverages existing attempts to assess the road space with regard to bicycling safety and infrastructure suitability. According to Loidl & Zagel (2014), expert assessment, crash black-

spot identification and user feedback are all suffering from conceptual and practical drawbacks, which make them inappropriate for a global, transferable and adaptable application. Thus, they developed a road assessment model that generates an indicator value, expressing the safety level for bicyclists. The general concept goes as follows: based on literature review, crash analysis, experts' and users' feedback contributing factors to objective (Beck et al. 2016) and perceived (Winters et al. 2012) safety threats are identified and compiled in a weighted assessment model (Eq. 1).

$$Index = \frac{\sum_{i=1}^{n} s_i \cdot w_i}{\sum_{i=1}^{n} w_i} \qquad (1)$$

The different values of each indicator are ranked and weighted (s_i). The influence of each indicator is reflected by a weight (w_i) that can be manually altered. The model in Figure 3 (Wendel 2015) is purely edge-based and considers the following influential factors (indicators): type of bicycle infrastructure, dedicated bicycling routes, road category, maximum speed, motorized traffic volume, number of lanes, pavement, parking, number of adjacent segments (indicating the complexity of junctions), car parking along the road, gradient, tram tracks and land use (Loidl & Zagel 2014). It is designed to be employed on the level of single road segments. For this, a topologically correct net-

work graph, together with attributes that adequately describe the road space are required. Before the model can be run, the respective data model and attribute structure of different data sources need to be considered and the definition of the indicators and their characteristic values accordingly adapted. The model can be fueled by commercial (such as from Here), authoritative (such as the Austrian GIP) and open (such as OpenStreetMap) data sources.

The design of the assessment model proposed by Loidl & Zagel (2014) facilitates iterative calibration and is spatially and functionally scalable, adaptable and produces comparable outputs. It can be used for a variety of purposes, ranging from planning to routing (see Loidl 2016 for application examples).

To the best of our knowledge, this model is the only one that is entirely network based, can be iteratively calibrated and adapted, and does not require manual inputs, but completely relies on existing data. The assessment model for the city of Augsburg by Jonietz & Timpf (2012) comes closest to Loidl & Zagel (2014). However, the differentiation between the values of the considered indicators is fixed and rather general classes in the model by Jonietz & Timpf (2012). Moreover, the model components are non-weighted, which does not sufficiently reflect the evidence from literature, which shows that the influence of influential factors vary significantly (Winters et al. 2011, Skov-Petersen et al. 2018). Con-

ceptually similar models are mostly based on spatial aggregates, such as grid cells, census districts or cities. The Bike Score index (Winters et al. 2016) is based on 100 m² raster cells and expresses "bike-friendliness". This index value is based on spatial data such as bicycle lane density, topography or number of amenities within a defined catchment area. Ma & Dill (2016) define bikeability as composite index where the following factors contribute: access to bicycle infrastructure, number of facilities within a specific distance, street connectivity and topography. An exception to the grid-based index calculation is the Network Safety Index (NSI), which was developed in the city of Amsterdam and provides very detailed information on safety performance of roads (de Kievit 2017). However, the required input data (investigation of the road profile every 25 meters) can only be acquired with a very high effort.

3.2 SPATIAL SIMULATION

Knowing when, where and how many bicyclists are on the road is decisive for practical questions, such as monitoring and management or planning and infrastructure building. In the context of bicycling safety, data on bicycle traffic flows is crucially important for the interpretation of incidents. Conclusions on safety risks cannot be drawn from bicycle crash data in the absence of a sound statistical population.

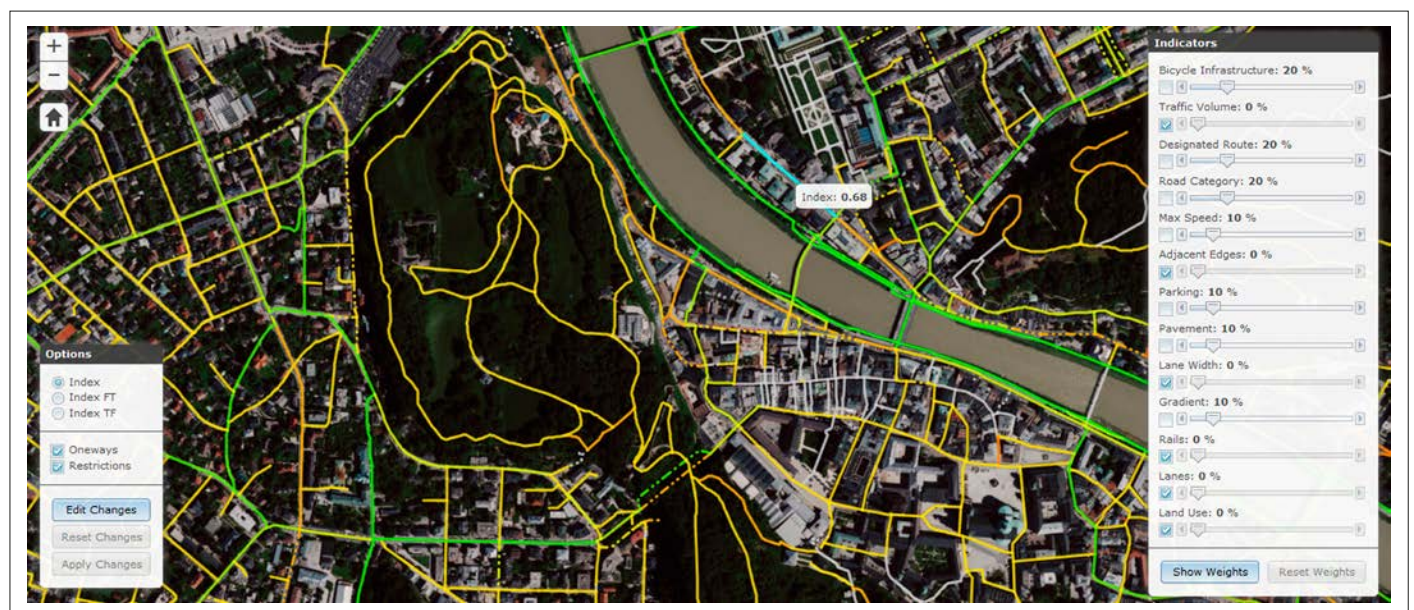Of course, the variety of well-established methods for simulating traffic flows is

Figure 3: Web-based assessment model of a road network (http://gimobility.sbg.ac.at/network-assessment/index.html, accessed 11/2017)
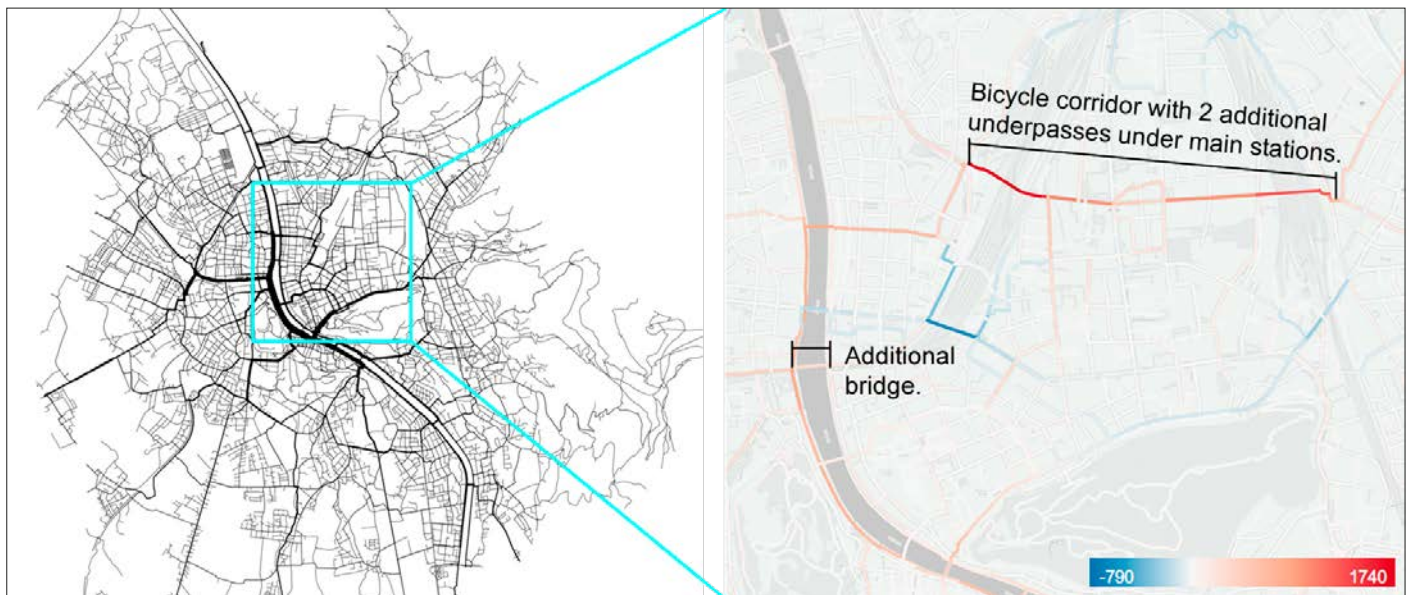
Figure 4: The left map shows the result of the simulation model. The effect (traverses per day) of infrastructure measures on the distribution of bicycle flows becomes evident in the right map.

huge. It ranges from demand-based models (McNally 2008) to flow-model simulations (Helbing et al. 2002), cellular automata models (Maerivoet & De Moor 2005) and agent-based models (Bazzan & Klügl 2014). However, the vast majority of these simulation models focus on public transit and car traffic. Traffic models for bicyclists and pedestrians are usually only available at the micro-scale. Because of this, investigations of bicycle crash data commonly use highly aggregated flow data (estimations based on mobility surveys or punctual counting stations) or alternative statistical populations, such as number of inhabitants. Using aggregated flow data for investigating geo-located crash data implicitly introduces the wrong assumption of evenly distributed bicycle traffic. Alternatively, bicycle crash data are aggregated as well and used in an epidemiological study design. However, in doing so the spatial information disappears and the spatial characteristics of bicycle crashes cannot be considered anymore. Using alternative statistical populations, such as the number of inhabitants, can lead to significant biases as well.

A major reason for why virtually no bicycle flow models exist on the scale level of a city (mesoscopic models) is the difficulty to describe and predict bicyclists' behavior. Bicyclists – similar to pedestrians – are by far less homogeneous than car drivers in many regards, such as travel speed, route prefer-

ences, interaction strategies etc. (Damant-Sirois et al. 2014, Füssl & Haupt 2017). Agent-based simulation models are suitable to reflect the multitude of individual behavior. In an ongoing research project (FamoS, https://gimobility.zgis.at/en/famos/) the concept proposed by Wallentin & Loidl (2015) is currently extended and an agent-based bicycle flow model, which simulates bicycling mobility at a spatio-temporal resolution of meters and minutes, will be released by the end of 2018. This simulation model brings together analytical capabilities (overlay, spatial statistics, network analysis) and the power of agent-based modeling. Spatial data on population metrics, facilities and road infrastructure as well as results from mobility surveys are used as inputs. The emergent bicycle flows result from simulated activities, mode choice and route choice for every single agent. We were able to simulate 150.000 agents for a whole day (24h) within approximately 5 hours of processing time. With this model it is possible for the first time to consider bicycle flows as statistical population in subsequent crash data analyses at the highest spatial resolution as well as testing for various interventions (infrastructure measures, promotion campaigns etc.), as it is illustrated in Figure 4.

3.3 SPATIAL ANALYSIS
Bicycle crashes are incidents that take place at a specific location and are partly

determined by space. Thus, the spatial analysis of bicycle crashes contributes to a better understanding of a multifaceted phenomenon. The current body of literature is rich of bicycle crash analysis. However, only in a minority of studies the spatial facet is explicitly considered (Vandenbulcke-Plasschaert 2011).

In a recent study Loidl et al. (2016a) used the geographic coordinates, which are attached bicycle crash reports, and the time stamp to explore urban bicycle crashes in the spatial and temporal dimension. In contrast to previous studies, the network-bound character of bicycle crashes was accounted for in the spatial analysis. With a purely explorative study design distinct patterns and temporal variabilities were revealed and further used for in-depth investigations. Many of these spatial and temporal variabilities (seasonal effects, clusters, regional particularities) would have remained undetected in any less detailed approach, although this information is crucial for targeted counter measures.

A substantial shortcoming of explorative studies of bicycle crash frequencies is their limited conclusion on risk or crash probabilities. For this, a statistical population with the same spatial resolution is required. Loidl et al. (2016b) used the outcome of the spatial simulation of bicycle flows (Wallentin & Loidl 2015) and related the geo-located bicycle crash data to the simulated traffic volume. Calculating crash
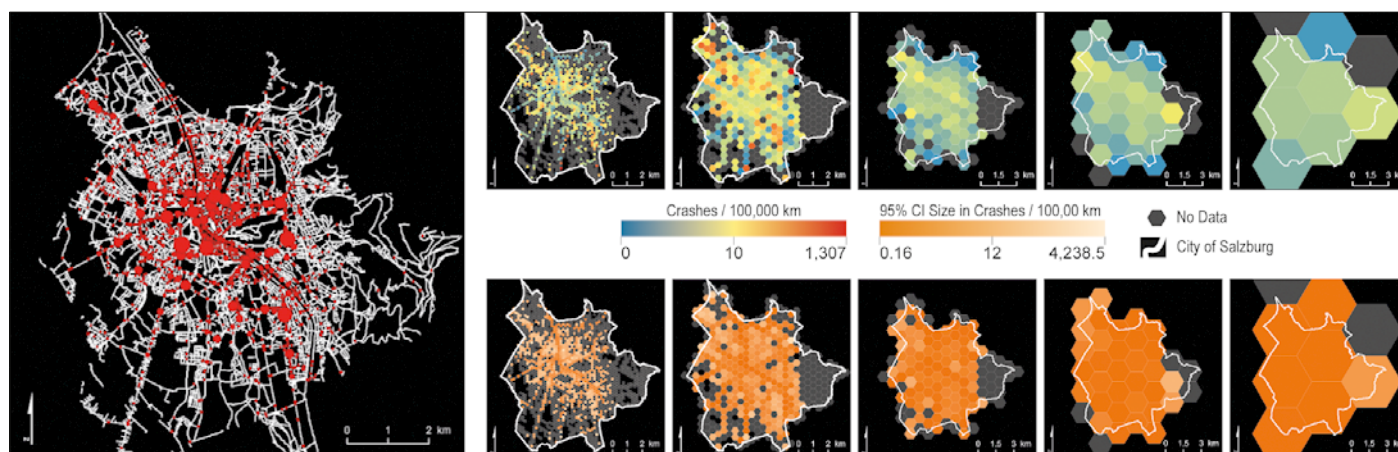
Figure 5: Crash locations in the city of Salzburg (left) where related to simulated traffic volumes. The patterns of crash rates changes with the level of spatial aggregation (top row of maps). Mapped confidence intervals (bottom row of maps) indicate the statistical robustness of rates.

rates on the local level inevitably results in a trade-off between accounting for the spatial heterogeneity of crash occurrences and the statistical robustness of results. Moreover, the modifiable areal unit problem (MAUP) impacts the results. In order to account for these spatial implications, Loidl et al. (2016b) mapped crash rates on different levels of spatial aggregation and linked it to mapped confidence intervals (CI). With this, the optimal size of the spatial reference units can be identified for a given study area. Plotting these two views (crash rate, CI) in a scatter plot allows for deriving information on MAUP effects; especially the scale effect becomes obvious.

In contrast to existing studies, which either rely on very vague flow estimations (Lusk et al. 2013), use aggregated data (Delmelle et al. 2012), or neglect the spatial dimension entirely (Martínez-Ruiz et al. 2015), Loidl et al. (2016b) is the first study that generates results at the local scale.

4 CONCLUSION AND FUTURE WORK

Bicycling safety is a central issue for any bicycling promotion initiative. I argued for why bicycling promotion needs to consider prevalent safety concerns and what spatial information can offer from a methodological perspective. The three identified methods of spatial modeling, simulation and analysis were then further discussed with reference to previous and ongoing research.

It became evident that spatial approaches lead to results that are relevant for a number of domains involved in bicycling promotion and safety research. Spatial models are able to integrate objective as well as perceived safety risks factors. Outcomes can then be linked to existing evidences from planning and engineering (physical environment) as well as to psychology (perception, emotions). The benefit of spatial in comparison to epidemiological models is twofold: firstly, the spatial configuration of influential factors (e. g. autocorrelation) can be directly considered. Secondly, results of the assessment model are mappable and thus, can be put into the respective spatial context. With reference to agent-based simulation models the strength of linking spatial analytical capabilities with simulation models was demonstrated. Again, data from very different domains (engineering to social science) are integrated in a spatially explicit simulation model, which facilitates an estimation of bicycle traffic at the highest possible resolution and can be used for simulating various interventions. Finally, the integrated analysis of geo-located crash locations and the results from the simulated bicycle flows, allows for in-depth analysis of crash rates at the local scale. This is especially important for targeted interventions and an efficient planning and implementation of safety measures, where aggregated statistics, such as crash rates for an entire city, are of minor relevance.

This paper demonstrates that the introduction of an explicitly spatial perspective into a research area that has been largely dominated by non-spatial domains and paradigms, such as bicycling safety in our case, leads to additional insights. However, several research questions, within GISci-ence as well as in bicycling safety research, remain open and need to be subject for further work:

▶ Any attempt that improves exposure data will directly improve any analysis of bicycle crash data. Consequently, better bicycle flow models need to be developed.

▶ It is evident from numerous studies that officially reported bicycle crashes represent only a fraction of all incidents (crashes and near-misses). Having a better data basis on safety threats could be turned into more reliable analysis results.

▶ The more data are being used as input in models, simulations and analyses, the higher gets the demand for data harmonization in terms of temporal and spatial resolution.

▶ Although perceived safety threats can be considered in spatial models, there is still a need for better understanding of safety perception on an individual level. Currently bicyclists are too often treated as homogenous group. Thus, the very different needs, preferences and perceptions are insufficiently reflected in bicycling safety research.

▶ Finally, research is needed on how to best turn evidences and research outcomes into behavior change. Without a better understanding psychological, social and cultural processes gained insight will not impact actual behavior.

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