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**Paris Lodron Universität Salzburg**

**Department of Geoinformatics**

**Applied Geoinformatics**

**Suitability analysis of mountainbike trails utilizing Strava metro**

**Master Thesis**

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Salzburg, Juli 2023

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## **Abstract**

# **Introduction: Scientific Relevance and Context**

## **The Scope of this Study**

## **Development of the sport of mountainbiking in Austria**

Mountain biking has grown in popularity in Austria over the past few decades due to technological advances in equipment, evolving riding styles, and the increased accessibility of trails. According to a study by Koemle and Morawetz (2016), the sport has steadily gained popularity in Austria over the last two decades. This growth can be attributed to a number of factors, including developments in bicycle technology and improved access to mapping software. The study by Pröbstl-Haider et al. (2018) highlights the increased preference for narrow singletrack trails and more challenging terrain among mountain bikers.

The use of e-mountain bikes has also made the sport more accessible to people in general and has likely contributed to the growth of mountain biking. The use of motorized mountain bikes has made previously inaccessible terrain and trails more accessible, leading to more mountain biking activity on trails not designed for bikers (Pröbst-Haider et al., 2018).

However, the rapid rise in the popularity of mountain biking, particularly on singletrack trails, has led to problems. One problem is the erosion of existing trails not designed for bikers. Another issue is the potential risk for other/all trail users, which can lead to user conflict. There is also the issue of crowding on the trails and environmental degradation (Pröbst-Haider et al., 2018).

While mountain biking is a relatively young sport, having been practiced since the mid-1980s, it has since progressed rapidly due to technological advances in equipment and evolving riding styles (Pröbst-Haider et al., 2018). In Austria, 33% of the population owns a mountain bike, and Germans make up the largest tourism source to Austria, with 39% of Germans owning a mountain bike (Pröbst-Haider et al., 2018). Given the implications of climate change, it has been encouraged to invest and develop all-season tourism more as a viable climate change mitigation and adaptation strategy, and mountain biking will play a role in this (Pröbst-Haider et al., 2018).

Mountain biking plays an important role in the portfolio of leisure and tourism activities in the European Alps, as well as in many other rural destinations (Pröbst-Haider, 2017). However, the accessibility of forests, alpine pastures, and open landscapes for mountain bikes differs significantly between the Alpine countries. While Germany, Switzerland, and Italy have opened their forests for mountain bikers, the Austrian Forest Act does not allow mountain biking on forest roads (Pröbst-Haider, 2017).

Despite the challenges, Austria boasts a large network of hiking trails and forest roads, making it an attractive destination for mountain bikers. A study by Pröbstl-Haider (2017) concludes that more appealing and well-maintained trails, as well as attractive leisure infrastructure, are needed. Improving trail construction standards that are adapted to different preferences, needs, and environmental conditions can also help (Pröbstl-Haider, 2017).

According to Salzburger Land Tourismus (2017), around 10% of tourists in Salzburger Land go mountain biking during their holidays. Furthermore, the Eurac study (2015) estimated that there are around 18.6 million potential riders for the alpine regions, with this number continuing to grow. To cater to this demand for mountain biking paths, the Land Salzburg has created a sample contract for official mountain bike paths, which includes a road liability insurance policy. Additionally, tourism offices pay usage fees to communities and landowners (Salzburger Land Tourismus, 2017). Despite this need for paths, there are currently only a few official mountain bike tracks in Salzburg, with the rare exception being along Lake Fuschelsee, which is maintained by the local tourist office there (Fuschelsee Tourismus GmbH, 2022).

## **Legal framework for mountain biking in Austria**

The legal framework for mountain biking in Austria differs between provinces, but the overarching legislation is provided by the Austrian Forest Act of 1975. This act allows Austrian citizens free access to forests but explicitly forbids driving vehicles or bicycles in the forest. As a result, cycling is forbidden on hiking trails or forest roads except when it is on publicly designated routes with prior approval from the entity responsible for management and maintenance for the road or trail. Cycling off-trail in a forest requires prior permission from the landowner. Landowners generally receive compensation in exchange for permitting cycling on their property. The provision of adequate insurance and signage on designated routes are also relevant aspects of the agreement, with the responsibility varying by province. Often, local tourism authorities are responsible for route signage, liability insurance, and maintaining contact with the landowners. (Pröbst-Haider et al., 2018)

## **User group conflict**

The increase in mountain bike traffic has led to conflicts among stakeholders, including hikers, landowners, hunters, conservationists, and other trail users (Pröbst-Haider et al., 2018; Lang, 2013; Zajc & Berzelak, 2016; Morey, 2002). Hikers often view cyclists as a threat due to their speed and quiet approach (Koemle & Morawetz, 2016; Goeft, 2001). On the other hand, cyclists tend to perceive walkers less negatively, simply noting them as a potential nuisance that can disrupt the quality of their experience (Cessford, 2003). Despite the considerable literature available on perceived conflict between hikers and cyclists on narrow trails, very few incidents have been documented that cite collisions between cyclists and walkers. Almost none of the thousands of incidents documented over several years on trails in the German Alps involve collisions between cyclists and walkers (Cessford, 2003).

However, despite the lack of documented collision incidents, the potential for conflict between cyclists and hikers, along with a negative perception of mountain bikers by hikers, remains a major roadblock for the establishment of mixed-use or shared trails in Austria (Koemle & Morawetz, 2016). Several mountainous tourism destinations in Austria report conflict between user groups, with cyclists and hikers being the most common (Pröbstl-Haider et al., 2018). Studies regarding cycling trends in Austria by Reichhart & Arnberger (2010), Von Janowsky & Becher (2002), and Wyttenbach (2012) confirm these observations, with conflicts between hikers and cyclists being among the most reported (Pröbstl-Haider et al., 2018).

According to research by Lang (2013), Austrian hikers consistently feel more disturbed by bikers than vice versa. In Tirol, a study found that 40% of hikers interviewed were disturbed by mountain bikers, and 30% felt threatened by them.

## **Study Area**

# **Methods**

## Data processing

### Raw Strava Metro data

Strava Metro data is a valuable resource for trail suitability analysis (Pröbstl-Haider et al., 2018). Strava Metro provides real-time data on bike rides and hiking activities, which can be used to analyze trail usage patterns. This data is particularly useful for identifying popular trails and areas where there is potential for user conflict. By analyzing Strava Metro data along with other data sources, researchers can gain a comprehensive understanding of trail usage patterns, which can inform trail development and management decisions (Pröbstl-Haider et al., 2018).

In addition, Strava Metro data can be used to understand the economic impact of mountain biking in a particular region. A study by Reichhart and Arnberger (2010) found that mountain biking had a significant economic impact in the Austrian Alps. The study found that mountain biking generated over €70 million in revenue and supported over 2,000 jobs in the region. Strava Metro data can be used to estimate the number of riders in a particular area, which can be used to estimate the economic impact of mountain biking in that region (Reichhart & Arnberger, 2010).

Overall, Strava Metro data provides valuable insights into trail usage patterns and the economic impact of mountain biking. When used in conjunction with other data sources, Strava Metro data can inform trail development and management decisions (Pröbstl-Haider et al., 2018).

* biking data from 2019,2020, 2021 and 2022 with hourly resolution of the bike rides per segment
* hiking data from 2019,2020, 2021 with hourly resolution of the hikers per segment
* the data from Strava gets matched to trails, paths, roads etc. from OpenStreetMap

### Data processing

Due to the hourly resolution, of all trail segments including all the road segments in the downloaded version of the data, several steps of data processing are necessary to create a dataset which can be further worked with.

The data downloaded from Strava Metro were single files with hourly resolution for a month respectively. 36 files for biking, 24 for hiking.

First of some discrepancies in the data needed to be resolved, such as differentiating naming of columns throughout the single 48 biking files and differences between the biking and hiking files. A detailed search for the inconsistencies and an extensive merging algorithm to include all naming and data variations was necessary. Some files included more columns then others, they also included ebike\_ride\_count and total tripcount (others only having forward and reverse trip count).

The raw data had a total of 31 columns, not needed columns where deleted and some columns (such as forward and reverse speed, or forward and reverse trip count), were merged.

Next the data was filtered spatially to cut out all the data regarding road segments. This was done by taking the Shapefile which only included the trails (for the most part). This was handled as a data frame and only data matching to the Shapefile edgeuids remained.

In R script: get file names for each file, specify which columns to keep, read file but if hour column doesn’t exist but date does rename date to hour. (Different column names in the later/earlier files) merge all files together, check if there are any NA values in the data frame, split date column into date and hour separately, create a new column with the matching weekdays and create a column with the total amount of bikerides (forward trip count and reverse trip count together. Replace 0 in the speed column as NAs as it heavily skews the speed distribution and the strava data put 0 where there was no speed data available.

Further get the mean speed for each row of reverse average speed and forward average speed. Delete no further used columns. Filter the data spatially with the shapefile, by reading the shapefile into R and filtering the bikingdata for matching edgeuids with the shapefile. The dataframe only consists of data with the edgeuids which are found also in the Shapefile.

For further data handling in the dashboard the statistics for each edgeuid was calculated for reduction of data.

## Dashboard

To enable data exploration and create a decision making tool, the solution was to be build a web-based application to allow multiple users to look at the data. Further benefits via cloud-computing are that it removes computation limits and provide on-demand load balancing (Li 2020)

Several iterations of the dashboard were produced, in the end the selected method was to write the Dashboard in R Shiny as solutions in JS and Python required more complicated solutions. By compling R code into HTML, CSS and JavaScript, Shiny has made it easy to develop web applications (Jia et al. 2022).

Building a Docker Image made sure that no requirement issues came up, as R and heavily relies on packages. Shiny is a dashboard package solution, furthermore the mapping was done via the leaflet package.

The dashboard loads the data locally and fetches the trails via a WFS from Geoserver. The latter is the biggest loading part of the application and CPU intensive as the WFS has 6000 single features.

### Leaflet map

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Automatisch generierte BeschreibungEin Bild, das Screenshot, Kreis, Farbigkeit enthält.

Automatisch generierte BeschreibungTo at least make the display faster, single segments are not displayed when zoomed out, instead they are displayed as clusters (see graphic X). And only appear when the user zooms into regional level.

### Color function

The biking and hiking data are put on the leaflet map as two different layers using the same WFS layer data. This is done due to it being the only working solution to have the color function according to both stats. Biking is displayed in a gradient blue according to the number of total bike rides on the respective segment, same for the hiking layer but the color gradient being red tones. When selecting both layers to be displayed, the segments where both hiking and biking are both high a purple tone appears, due to the opacity being at 0.6. This allows the user to see where hiking or biking is predominant.

### Filtering functions

The filtering option for the segments with the highest usage utilizes a column in the dataframe which has the length for each segment in km. For example when filtering for the 100km trails with the most bike rides, the dataframe gets sorted after the highest trip count and a cumulative sum of the kilometer column gets created and the segments until 100km in the cumulative sum are reached are then displayed. Same applies for the hiking data.

* Info on segment edgeuid, total hikes and total rides are displayed in a popup and the side tab
* Plots on hourly, weekly and monthly distribution on either all segments on the map (when no segment is selected) or a the selected segment for both hiking and biking
* Add graphic of plots

## Pipeline

Using Docker makes the work more easily reproducible, as it makes it independent from package dependencies. Using Docker with AWS Beanstalk makes the Shiny app scalable and easy to deploy. With the Dockerfile, AWS Beanstalk can create new instances of the app quickly enabling to handle increase or decrease of traffic. Docker also isolated the Shiny app in a container, making it more secure.

## Docker configuration

The repository has two Dockerfiles, one the Dockerfile which builds the Docker image and the other the Dockerfile.aws.json, which Beanstalk later needs for deploying on the server.

The Dockerfile for the application uses the Docker image rocker/shiny:latest. This image is created and maintained by the rocker project, which provides Docker images for the R environment. The shiny image includes the Shiny Server and the necessary R packages to run a Shiny app.

The Dockerfile looks for updates of the base system and installs necessary libraries, the system-level dependencies for the packages which Shiny needs are installed. Additionally libgdal-dev libgeos-dev and libproj-dev ensure that the dependencies for spatial data processing are met.

For trouble shooting, the shiny error logs as set to the console for immediate feedback when developing.

Next the Dockerfile copies the app.R and the data folder from the local or Github repository to the Docker image built. Additionally, all the R packages need to be installed into the Docker image. This is the step that takes longest when building the image. And finally, the container should run on port 80 when the container is started.

Additionally, it has a Dockerfile.aws.json file, the file simply specifies how AWS should handle the Docker container. It tells AWS that it is a single container application, the name of the application and the port.

## Github Action

The deploying process is automated using Github, Docker and AWS Beanstalk and Github Actions.

The application is in a Git repository, synched to GitHub. The repository has a Github Actions workflow that automates the process of building Docker images, pushing them to Docker Hub and deploying them on AWS Elastic Beanstalk.

Firstly, the workflow is triggered on a Git push event to the masters branch. The workflow runs on a Ubuntu virtual machine provided by Github Actions. It starts by cloning the repository to have access to the source code and Dockerfile. Then it authenticates with Docker Hub using provided credentials stored in GitHub Secrets. Next, it build the Docker Image using the Dockerfile in the repository and tags it with an additional tag as “latest”. The Docker Image then gets pushed to the Docker Hub repository to make it available externally.

For deploying on AWS Beanstalk, authentication keys are stored again in Github Secrets. Other then that the application name, environment name and version label, which were previously initialized, need to be specified for deployment.

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# **Results**

# **Discussion**

* Data about the surface and road type can be improved. Manually selecting/deleting asphalt roads to extract dirt tracks is limitless.
* Large amount of data
* Temporal filtering was taken out, as it increases the data size by a multiple
* Temporal filtering is interesting to explore but in the end the information it delivers is limited in the influence of trail selection. Information about the rough temporal distribution of trips, is kept through the segment statistics in hourly, weekly, monthly, yearly distribution.
* Interesting would be more information about the tracks. Such as the width as that would exclude very narrow trails which are heavily frequented by hikers.

## **Drawbacks and Future Improvements of this Study**

# **Conclusion**

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