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Research paper

# Assessing spatial characteristics to predict DRT demand in rural Switzerland

Sebastian Imhof, Kevin Blättler *

*Competence Center for Mobility, Lucerne University of Applied Sciences and Arts - Business, Rösslimatte 48, 6002, Lucerne, Switzerland*

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ABSTRACT

The niche market segment of demand responsive transport (DRT) services is meant to overcome structural economic problems of currently cost ineffective public transport (PT) services in rural areas. Simulation studies for mainly urban DRT services showed that demand for DRT trips is correlated with spatial characteristics. More knowledge of spatial characteristics of rural settings and their influence on DRT trips is necessary.

In this study, trip data of a rural DRT service called mybuxi is used. Machine learning is applied for a better understanding of spatial characteristics of DRT demand in two different rural settings of the mybuxi service. Herein, the transferability from one mybuxi setting to the other is then tested.

Results show that the number of inhabitants is the most important spatial characteristic for the prediction of DRT demand, followed by the distance to a train station and the presence of a restaurant in a given zone. The quality indicator of PT had low or no predictive power. The study shows that both DRT service areas experienced an increase in accessibility. For future transport planning, the increase in accessibility by DRT services in different rural areas must be taken as a legitimation for these services to be implemented instead of line-bound PT services.

## 1. Introduction

Public transport (PT) operators face the problem that sparse population and extensive surface area only allow low service frequency which in the end leads to an unattractive service availability for the population. Rural PT services can be highly cost-ineffective, and the operators need additional public subsidies to maintain the services (de Jong et al., 2011). Mounce et al. (2020) call this set of circumstances the “rural mobility problem”. To overcome this problem, flexible demand-responsive transport (DRT) services gained the interest of PT operators as well as researchers. DRT services are meant to strengthen rural transport services, as they allow a higher accessibility in rural areas compared to fixed route services with buses (Avermann & Schlüter, 2019; Coutinho et al., 2020). Especially in the case of transport agencies trying to sustain a certain service level for the passengers despite low ridership, DRT services may be a better solution than fixed route services (Volinski, 2019). DRT services so far are considered niche services that either operate as a replacement or in concurrence to traditional public transport services (Sharmeen & Meurs, 2019). Important success factors of DRT services are their integration in a public transport mix and their ability to fill gaps in accessibility in areas with low PT demand (Daniels & Mulley, 2012). A combination of future autonomous DRT services with existing mass transportation services such as commuter railways may help to increase PT ridership in rural areas (Imhof et al., 2020).

Due to their higher flexibility, DRT services can specifically contribute to a decrease in personal car usage in rural areas (Sörensen et al., 2021) and to reducing social exclusion of mobility-disadvantaged persons (Nykiforuk et al., 2021; Vitale Brovarone, 2021). Previous studies showed that, in general, persons with low income (Kuhnimhof et al., 2012), specifically young adults (e.g. Buehler & Hamre, 2015; Molin et al., 2016; Schulz et al., 2021) and retired persons (Scheiner et al., 2016) can profit from easy PT access and are more aware for multimodal trips (Buehler & Hamre, 2015) which is important for trips combining DRT and PT like train services. In Switzerland, Thao et al. (2023) found that especially elderly people and people without access to a car, use DRT services in rural areas more often compared to adults in working age and people with access to a car. In effect, governments see in DRT a mean to increase accessibility and social inclusion at the same time (Davison et al., 2012).

However, research showed that many current rural DRT services are

* Corresponding author.
*E-mail address:* kevin.blaettler@hslu.ch (K. Blättler).

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not economically viable (Currie & Fournier, 2020). Spatial characteristics can be influential on the number of trips realized in certain areas, yet research on spatial characteristics of flexible transport services so far concentrated mainly on simulations and statistical models of large-scale flexible transport services' trip data in urban areas (Guidon et al., 2020; Zwick & Axhausen, 2022). Population and job density as well as the distance to a city center were found to be crucial factors influencing trip origins and destinations in DRT services (e.g. Weckström et al., 2018; Zwick & Axhausen, 2022). Jain et al. (2017) additionally showed that, for the Greater Melbourne region, spatially differing socio-demographic patterns as well as PT performance are essential factors to be considered for predicting the usage of a DRT service. Yet, it is still unclear whether accessibility measures influence the usage of a particular DRT service.

To further understand how rural DRT services can be scaled up, more knowledge of spatial characteristics in rural settings and their influence on DRT demand are needed. In this study, trip data of the rural DRT service called *mybuxi* is used. We predict DRT demand with spatial characteristics using the machine learning algorithm 'random forests'. We use this model to test the transferability from one mybuxi setting to another by training the algorithm in a perimeter, where the service is established and then predict demand in a new perimeter.

So far, several studies using simulation methods have highlighted the importance of spatial characteristics on the performance and quality of DRT services. According to a simulation by Ronald et al. (2013), the level of service of a DRT service is affected by the spatial distribution of demand. Diana et al. (2007) found that DRT services, compared to PT services, have lower emissions where demand is low and high levels of service quality sought. The usage of small vehicles may therefore outperform line-based services. Scott (2010) highlights the suitability of DRT services where transport demand is low. He distinguishes between following factors influencing low demand: time of day; day of week; low-density land-use patterns like suburban or rural areas. Spatial characteristics further influence the pooling rate of flexible transport solutions such as DRT. Brown (2019), Gehrke et al. (2021) and Li et al. (2019) all found that in areas of high population density there is a greater likelihood that a pooled service option will be chosen by passengers. For a Swiss ridesharing scheme in a rural context, Thao et al. (2021) found no association between land-use diversity and demand for ridesharing trips.

These studies using simulations do not offer more in-depth information on which spatial patterns of demand are found in real-world DRT services and to their influence on the sustained operation of the service. Currently, only sparse literature on this topic exists. Sörensen et al. (2021) highlight the spatial patterns of a rural DRT service in Germany and found that trip frequency related to the population size of neighboring villages or cities. In their case study, the topography had an impact on the resulting corridors that developed. Alonso-González et al. (2018) showed that users of a DRT service in the Netherlands experienced a high improvement in accessibility compared to traditional PT services, highlighting that the accessibility gains are the highest in underserved areas. Throughout the present article, accessibility is understood as a multi-dimensional concept that takes into account, how members of society can reach their desired destinations (Mulley et al., 2012).

The rest of this paper is structured as follows: in chapter 2, the data sources for this study are presented, followed by a descriptive statistic on the data. Chapter 3 is dedicated to the chosen methodological approach. Results in chapter 4 then describe the findings on the spatial interactions of the two chosen mybuxi service areas and whether the findings on one service area are transferrable to the second service area. The paper then concludes with a discussion of the key findings as well as the limitations of the study.

## 2. Context and data description

### 2.1. Context

Mybuxi is a start-up company dedicated to providing rural DRT services. The company was founded in 2018 and set up four different DRT services in rural Switzerland, so far. Two services in rural parts of the canton of Berne are examined in this paper. Both services use virtual stops based on which passengers can choose origin and destination stop individually. The virtual stops are evenly distributed over the entire service area in populated areas as well as places of touristic interest. Upon requests of the local population and enterprises, virtual stops can be added or eliminated in the mybuxi system. Operating in areas where car dependency is high mainly because of lack of highly frequent PT services, the main goal of the mybuxi service is to provide an alternative to the private car usage. Especially elderly people or school children in rural areas are target groups of the service.

The first service started in April 2019 in the Herzogenbuchsee Region in the municipalities of Herzogenbuchsee and Niederönz. Two municipalities, Bettenhausen and Thörigen, joined the service two years later. However, in these two municipalities mybuxi operates only in the evening and with fixed stops. For keeping a consistent dataset, we exclude these two municipalities of the analysis. In the analysis of the Herzogenbuchsee area, 46′389 trips were included.

The second perimeter lies in the Emmental Region with six rural municipalities involved. There, the service started in September 2020. Due to political regulations, the operation is different in the municipality of Burgdorf compared to the other five municipalities (e.g. pick-ups from the train station are not allowed before 19 o'clock). Therefore, we also exclude this municipality from the analysis. In the Emmental area, 6′485 trips were included in the statistical analysis.

Both service areas are important pilot services for mybuxi to gain helpful experience for future expansions to other rural areas. The continuation of both services after the first two pilot years underscores the current success of mybuxi in these areas. In both perimeters, the service started with one minivan to cover the demand; in the Herzogenbuchsee area, a second vehicle was necessary after the first year of service. In the Emmental area, a second vehicle is used to cover peak-time demand. Today, the service is not economically viable and is therefore relying on public subsidies and private sponsorships. In Switzerland, the public subsidies for DRT services are lower than subsidies for traditional bus services.

The service in both areas is reliant on volunteer drivers, receiving 50 Swiss Francs for a shift of 4–5 h. For the Herzogenbuchsee area, a user must pay 4 Swiss Francs per trip; for the Emmental area, a trip costs a user 10 Swiss Francs. Average trips in the Emmental area are much longer than in the Herzogenbuchsee area. Currently, there is no possibility to integrate a DRT service in the public transport system and the nationwide ticket fare system due to regulatory constraints.

### 2.2. Data description

Input data were collected from various sources. The DRT operator mybuxi provided the demand data for all trips in both regions examined. For the spatial data, we used data provided by the Federal Statistics Office (FSO) as well OpenStreetMap (OSM) data (OpenStreetMap Contributors, 2022). Additionally, we gathered data from geospatial analysis for distance measurements (Openrouteservice, 2022).

For both service areas, we created a 300 × 300-m raster covering both service areas. This resulted in 175 zones in the perimeter of the Herzogenbuchsee area as well as in 915 zones for the perimeter of the Emmental area. For each zone, pick-ups and drop-offs with the mybuxi DRT service were plotted. The pick-ups and drop-offs per zone are the dependent variables. We use the number of trips (and not the number of passengers), since we assume that pooling rather happens in areas with higher population density. The spatial data per zone acts as predictor.

**Table 1**
Independent variables: spatial data.

| Data | Data source |
|---|---|
| Population size per hectare | (Federal Statistical Office (FSO), 2021b) |
| Number of employees per hectare | (Federal Statistical Office (FSO), 2021a) |
| Number of workplaces per hectare | (Federal Statistical Office (FSO), 2021a) |
| Quality of PT, ordered into five categories:<br>A) Very good PT coverage<br>B) Good PT coverage<br>C) Moderate PT coverage<br>D) Poor PT coverage<br>E) No PT coverage | (Federal Office for Spatial Development (FOSD), 2022) |
| Points of interest<br>- Hotels<br>- Restaurants (incl. bars)<br>- Health care<br>- Schools<br>- Shops | (OpenStreetMap Contributors, 2022) |
| Distance to next train station (in km) | Based on Openrouteservice (2022) |

Table 1 lists the spatial data used.

A centrality variable was introduced to better understand in which way rural land-use patterns are explaining demand for DRT services. We therefore calculated the distance between each zone's centroid and the nearest train station, with the distance as result of the variable "Distance to next train station (in km)". The introduction of the variable "Quality of PT" additionally gives an indication on the accessibility of each zone with PT. PT stops are not included in the model, as they are covered by the PT quality in each zone.

### 2.3. Descriptive statistics

Table 2 describes the number of pick-ups and drop-offs per zone –the dependent variables - for the Herzogenbuchsee and Emmental areas. In the Herzogenbuchsee area, the mean for pick-ups and drop-offs per zone is higher. In the Emmental area, comparatively more zones do not have any pick-ups or drop-offs. That is, the distribution of pick-ups and drop-offs is more left skewed compared to that of the Herzogenbuchsee area.

Fig. 1 shows the population density in both examined areas, the Herzogenbuchsee and Emmental areas, and Table 3 describes the statistical distribution of the population as well as the employees per zone. In the Herzogenbuchsee area, the area is populated densely with a higher concentration of the population around the train station in the middle of the area. At the boundaries of the perimeter, population density is fading out. Overall, the mean population (see Table 3) is higher, the mean employees per zone lower than in the Emmental area. In the Emmental area, the population is more dispersedly distributed. Around both train stations in the Emmental area, the population density is the highest, like in the Herzogenbuchsee area. Inside the Emmental area, due to a topographically complex situation, many zones have no or small populations. The perimeter of the Emmental area is dominated by a hilly topography with many farms, resulting in a scattered settlement structure. The scattered distribution of small farms explains the slightly higher number of employees per zone in the Emmental area.

**Table 2**
Description of pick-ups and drop-offs in Herzogenbuchsee and Emmental areas.

| Variable | Min | 1st Quartile | Median | Mean | 3rd Quartile | Max |
|---|---|---|---|---|---|---|
| Herzogenbuchsee area | | | | | | |
| Number of pick-ups per zone | 0 | 0 | 1 | 267.5 | 69.5 | 18′078 |
| Number of drop-offs per zone | 0 | 0 | 2 | 265.1 | 103 | 8′996 |
| Emmental area | | | | | | |
| Number of pick-ups per zone | 0 | 0 | 0 | 7.2 | 0 | 1′944 |
| Number of drop-offs per zone | 0 | 0 | 0 | 7.1 | 0 | 984 |

Fig. 2 shows the geographical distribution of drop-offs in both perimeters studied. In both perimeters, the zone in which the train station is situated has the most drop-offs (Herzogenbuchsee area: 8′996 drop-offs; Emmental area: 984 drop-offs at South-Eastern train station). The same pattern is observed for pick-ups (Fig. 3) (Herzogenbuchsee area: 18′078 pick-ups; Emmental area: 1′935), therefore the presence of a train station appears to be a factor for increased pick-ups and drop-offs. Fig. 4 presents the daily temporal distribution of trips. In the Herzogenbuchsee area, morning peak is reached between 10 and 11 o'clock, evening peak is reached between 16 and 17 o'clock The morning peak in the Emmental area is reached between 8 and 9 o'clock and in the evening between 17 and 18 o'clock. This indicates that trips in the Emmental area may be associated with commuting purposes.

The much denser distribution of pick-ups and drop-offs in the Herzogenbuchsee area than in the Emmental area (see Figs. 2 and 3) may be explained by the dense settlement structure (see Fig. 1). The demand for trips in the Emmental area is more disperse. Additionally, due to the larger perimeter in the Emmental area, trips are comparatively longer in time and distance than in the Herzogenbuchsee area.

## 3. Methods

We use the random forests algorithm to predict demand for the DRT services within and across areas. Random forests are created by bootstrap aggregating ("bagging") single decision trees. Decision trees split the set of possible values of the predictors X into nonoverlapping subregions. The average outcome in the subregions is then the prediction for all observations within the subregions. Bagging the decision trees then decreases variance and the risk of overfitting and hence, increases predictive accuracy. Additionally, random forests force each split to consider only a random subsample of predictors to decorrelate the splits from each other (James et al., 2013).

Based on this subsampling of predictors in each split, a variable importance score can be calculated. The variable importance score shows the difference between the average prediction error when a predictor is considered and the average prediction error when the same predictor is left out. For the most important variables, we plot the partial dependency between the spatial variable and the demand prediction. We point out that we do not analysis the causal effects of the spatial variables on demand, but simply their capability of forecasting demand. That is, even though random forests overcome multicollinearity by nature, correlation between the spatial variables can influence the relative importance score and the partial dependence plots. We use the randomForest package by Breiman et al. (2022) in R to implement random forests based on growing 500 decision trees. Due to the medium size sample, results are obtained using bootstraps to prevent possible overfitting. We present the distribution of the means of 100 samples.

To equalize the level of observed values, we subtract the mean and divide the result by the standard deviation when analyzing the predictive power across perimeters. With this approach, we get standardized values, such that all variables have a mean of zero and a standard deviation of 1. Additionally, no zone has a PT quality classified as A in the Herzogenbuchsee area. Therefore, when testing the transferability from Herzogenbuchsee to Emmental, we bound the quality indicator of PT at the upper limit, such that the quality classes A and B are merged.

## 4. Results

First, we split the dataset from the Herzogenbuchsee and Emmental areas into a training and test set separately to recognize spatial patterns within areas. Second, we use the Herzogenbuchsee area as training set and the Emmental area as test set and display which spatial characteristics predict DRT demand across perimeters the best.

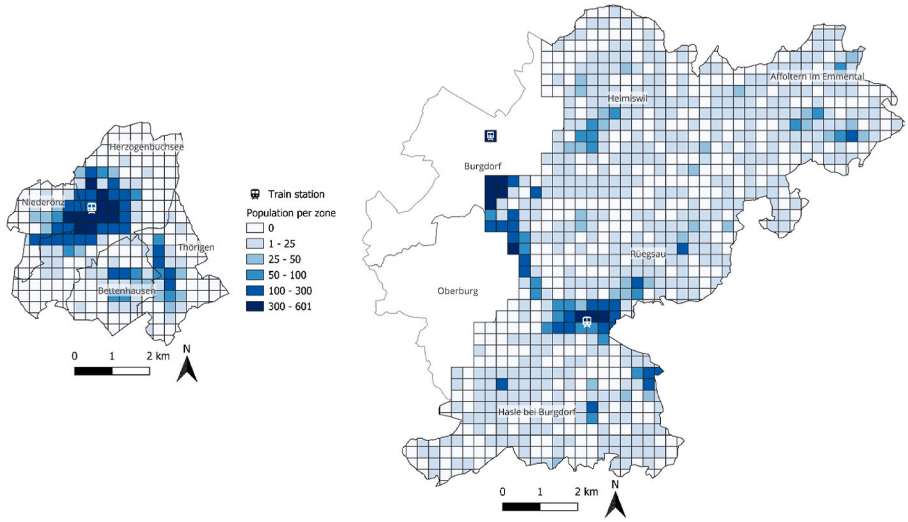


**Fig. 1.** Population distribution in the Herzogenbuchsee (left) and Emmental (right) areas.

**Table 3**
Statistical distribution of population size and employees per zone.

| Variable per area | Min | 1st Quartile | Median | Mean | 3rd Quartile | Max |
|---|---|---|---|---|---|---|
| Population size per zone | | | | | | |
| Herzogenbuchsee | 0 | 0 | 0 | 51.6 | 26.5 | 483 |
| Emmental | 0 | 0 | 3 | 11.1 | 8 | 377 |
| Number of employees per zone | | | | | | |
| Herzogenbuchsee | 0 | 0 | 0 | 2.4 | 0 | 303 |
| Emmental | 0 | 0 | 0 | 5 | 4 | 296 |

### 4.1. Prediction within perimeters

Table 4 shows the importance of the spatial variables to predict the number of pick-ups and drop-offs in the Herzogenbuchsee area. Within this perimeter, the most important variable is the number of inhabitants, followed by the distance to the train station. Among the points of interests, restaurants and health care facilities have some predictive power. The quality indicator of PT has low predictive power. Finally, patterns between pick-ups and drop-offs are similar.

Table 5 shows the importance of the spatial variables to predict the number of pick-ups and drop-offs in the Emmental area. Within this perimeter, the most important spatial variables are the number of restaurants, the number of employees and the number of inhabitants. Again, the quality indicator of PT has low predictive power and patterns between pick-ups and drop-offs are similar. With a word of caution, we excluded the municipality Burgdorf, where the main health facility in the region is located. That may be why the variable "health care" has no predictive power.

### 4.2. Prediction across perimeters

Finally, we test whether DRT demand can be predicted in new perimeters. Therefore, we use the pioneer perimeter in Herzogenbuchsee for training the algorithm and then test how accurate the estimator predicts demand in Emmental. The results suggest that the number of inhabitants and the distance to the train station are the two spatial characteristics that are important in both perimeters (see Table 6). The dependent variable's variance is explained by 8% for pick-ups and 25%, respectively. In other words, we can predict about 25% of the variance of drop-offs between zones.

Figs. 5–7 illustrate how demand prediction changes, when the values of the important predictors alter. Fig. 5 indicates that the more

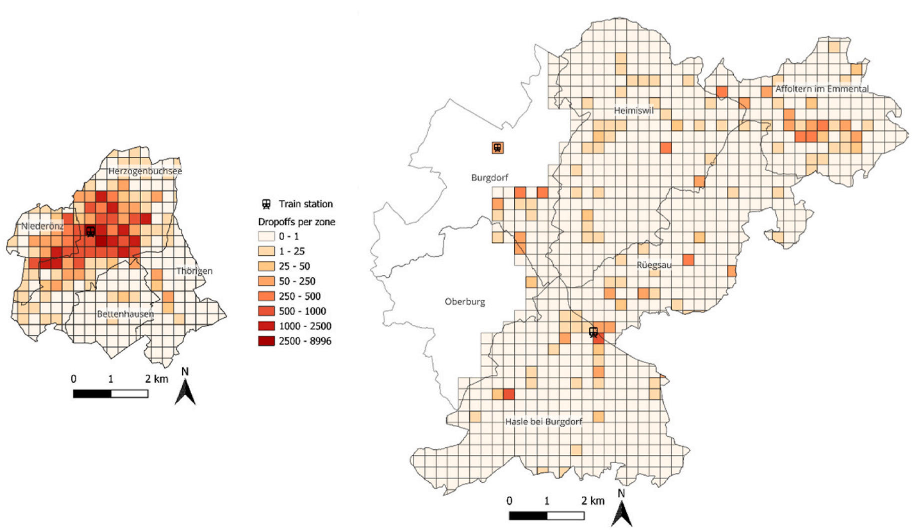


**Fig. 2.** Spatial drop-off distribution in the Herzogenbuchsee (left) & Emmental (right) areas.

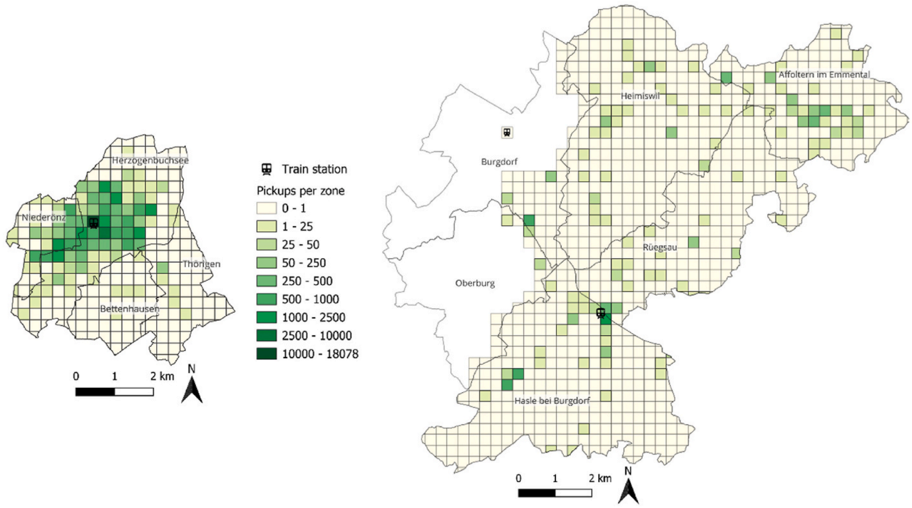


**Fig. 3.** Spatial pick-up distribution in the Herzogenbuchsee (left) and Emmental (right) areas.

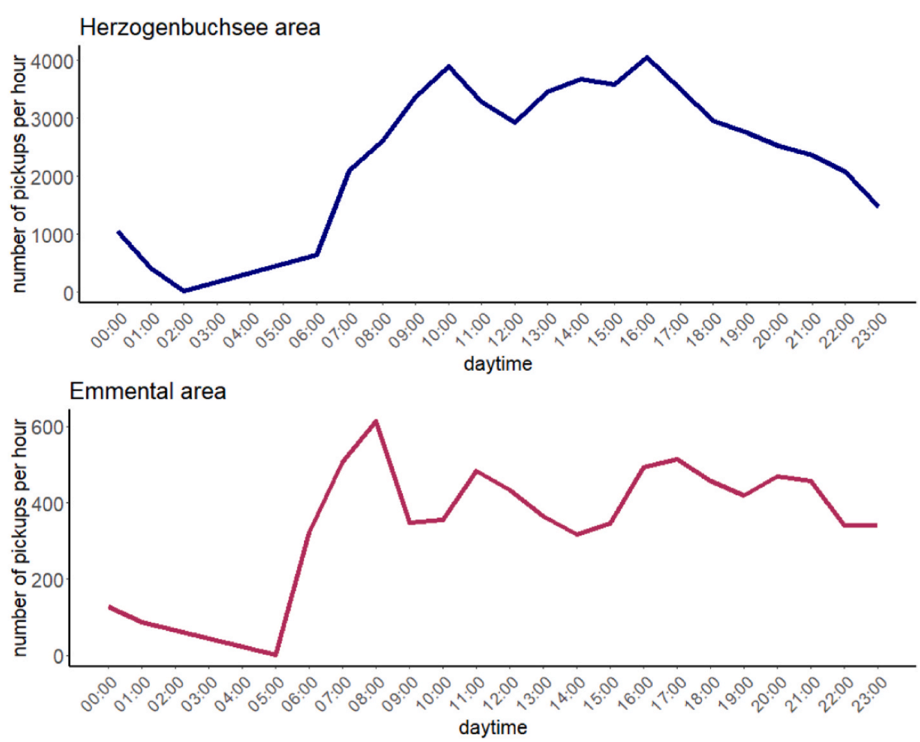


**Fig. 4.** Temporal distribution of trips in Herzogenbuchsee (up) and Emmental (down) areas over the entire project time.

inhabitants live in a zone, the higher the demand prediction. Whereas the partial relationship between population size and DRT demand is approximately linear, we observe in Fig. 6 a non-linear relationship between the distance to the train station and the DRT demand. Fig. 6 shows that demand prediction increases tremendous right at the train station. Furthermore, Fig. 7 displays that prediction goes up with the occurrence of a restaurant; however, the quantity of restaurants does not seem to matter. That is, if this predictor is used for a splitting rule, the data is mostly split between zones with and without restaurants.

## 5. Discussion & conclusion

This paper examined the spatial demand characteristics of the rural DRT service called mybuxi in two of its operating perimeters. Machine learning was used for a better understanding of spatial characteristics of DRT trips in these two rural areas with different settings (dense vs. sparse populations, small and flat vs. large and hilly areas). Unlike other simulation studies in this field of research, these two rural cases are analyzed using data of a real-world DRT service. Further on, the paper showed how random forests algorithms can be used in the context of such rural DRT services. In particular, the transferability from one mybuxi setting to the other was investigated.

Overall, the number of inhabitants was found to be the most important spatial characteristic to predict DRT demand across perimeters. Increasing number of inhabitants per zone lead to higher demand predictions. This may be explained as increasing the number of inhabitants increases the number of potential users, underscoring the principle of the “rural mobility problem” caused by low population size and density (see Mounce et al. (2020)). The finding on the interrelation between population density and demand for trips is in line with previous

**Table 4**
Variable importance in the Herzogenbuchsee area.

| Predictor variable | Pick-ups | | Drop-offs | |
|---|---|---|---|---|
| | Variable importance (% decrease of prediction error) | Relative variable importance | Variable importance (% decrease of prediction error) | Relative variable importance |
| Population | 12.53 | 1 | 16.21 | 1 |
| Distance to train | 8.13 | 0.65 | 9.08 | 0.56 |
| Restaurant | 4.12 | 0.33 | 5.87 | 0.36 |
| Health care | 3.90 | 0.31 | 5.40 | 0.33 |
| Shop | 3.59 | 0.29 | 3.90 | 0.24 |
| Quality of PT | 2.37 | 0.19 | 2.72 | 0.17 |
| School | 1.98 | 0.16 | 1.76 | 0.11 |
| Hotel | 0.00 | 0.00 | 0.00 | 0.00 |
| Employees | −0.77 | – | −0.67 | – |

**Table 5**
Variable importance in the Emmental area.

| Predictor variable | Pick-ups | | Drop-offs | |
|---|---|---|---|---|
| | Variable importance (% decrease of prediction error) | Relative variable importance | Variable importance (% decrease of prediction error) | Relative variable importance |
| Restaurant | 7.94 | 1 | 9.25 | 1 |
| Employees | 6.96 | 0.88 | 8.22 | 0.89 |
| Population | 4.88 | 0.62 | 7.19 | 0.78 |
| Distance to train | 4.19 | 0.53 | 6.03 | 0.65 |
| Shop | 3.37 | 0.42 | 4.11 | 0.44 |
| Quality of PT | 1.25 | 0.16 | 2.80 | 0.30 |
| Hotel | 0.95 | 0.12 | 1.09 | 0.12 |
| School | 0.28 | 0.04 | −0.14 | – |
| Health care | 0.00 | 0.00 | 0.00 | 0.00 |

**Table 6**
Variable importance across perimeters.

| Predictor variable | Pick-ups | | Drop-offs | |
|---|---|---|---|---|
| | Variable importance (% decrease of prediction error) | Relative variable importance | Variable importance (% decrease of prediction error) | Relative variable importance |
| Population | 3.61 | 1 | 12.11 | 1 |
| Distance to train | 3.26 | 0.90 | 5.97 | 0.49 |
| Quality of PT | 1.22 | 0.34 | 1.03 | 0.08 |
| Restaurant | 1.03 | 0.29 | 4.35 | 0.36 |
| School | 0.50 | 0.14 | 1.54 | 0.13 |
| Health care | 0.23 | 0.06 | 3.82 | 0.32 |
| Shop | 0.17 | 0.05 | 1.04 | 0.09 |
| Hotel | 0.00 | 0.00 | 0.00 | 0.00 |
| Employees | −1.70 | – | −2.01 | – |

research on urban flexible transport services (e.g. Weckström et al., 2018; Zwick & Axhausen, 2022).

The second important variable was found to be the distance to the train station. We observe a non-linear relationship between the distance to the train station and the number of trips, with demand greatest closest the train station. This observation is in line with the literature that highlights the importance of integrating DRT into a PT mix (Daniels & Mulley, 2012). In the planning process of new DRT services, these first two findings are important for the definition of new perimeters. For a successful and viable DRT service in a rural setting, the inclusion of more densely populated areas as well as integrating a train station in form of a hub station are crucial factors. If a region is even less populated than some parts of the Emmental area, there may additional factors (e.g. tourism) that could determine the demand for trips in a perimeter that were not examined in this study. Here, further research on spatial characteristics of new perimeters with other spatial preconditions will be necessary.

Among points of interest, the presence of restaurants has the most predictive power. That may be interlinked with the location of restaurants, as they are often situated in areas where social life takes place. They are often close to the village center, tourist attractions or health-care facilities. This finding may be important for the planning of the service area of a new rural DRT system, too, especially when virtual stops in an app instead of physical stops like with buses are being used. Restaurants can be important pick-up and drop-off stops in these systems, also regarding the ability to pool rides. And for restaurants and shops around them, for their customer base the reachability may be increased. Especially in rural areas, where restaurants and shops often face economic pressure, DRT services may help to keep or increase their business. The quality indicators of PT were all found to have low or no predictive power as the predictions for zones with poor, moderate and good PT quality are similar. Based on this finding, we draw the conclusion that the DRT services increase the accessibility of all zones within the two perimeters.

In conclusion, the DRT service shows similar patterns than PT services in different rural settings. Therefore, understanding the spatial characteristics is crucial to optimize benefit from schedule flexibility and small vehicle size of DRT services and hence, increase not just cost efficiency but also accessibility. For research and future policies on rural DRT services, this is a crucial finding. Future research must continue to examine the interaction between rural DRT services and bus transport services. Especially the increase in accessibility with a DRT service legitimates future public subsidies and if enough capacity is available, the DRT services may replace the traditional bus services. Future research should continue to examine further potentially influential spatial factors such as touristic spots or sport sights that may influence the demand for a rural DRT system.

## 6. Limitations

Our interpretation of the success factors for DRT services is based on the capability of predictors to forecast demand and not on the analysis of causal effects. In other words, we show that some spatial characteristics (e.g., restaurants) can predict demand DRT, but we do not analyze whether these spatial characteristics caused the DRT trip (e.g., people going into the restaurant after drop-off). The important spatial characteristics may be interlinked with other non-observable spatial characteristics (e.g., restaurants are often situated where other activities take place).

Additionally, by fitting spatial to demand patterns, we can hint towards increasing accessibility within perimeters, however we cannot quantify the number of trips that were made complementary and supplementary to the PT service. Future studies should focus on this research question.

Another limitation is that mybuxi operates in the Emmental area with less virtual stops, around 200 of them, than the Herzogenbuchsee area with around 1′000 virtual stops. Therefore, we cannot be sure that the trip before the pick-up and after the drop-off starts respectively ends within the same zone. If that is not the case, the predictions would be misleading. Spatial regression algorithm that account for spatial dependencies might resolve this concern.

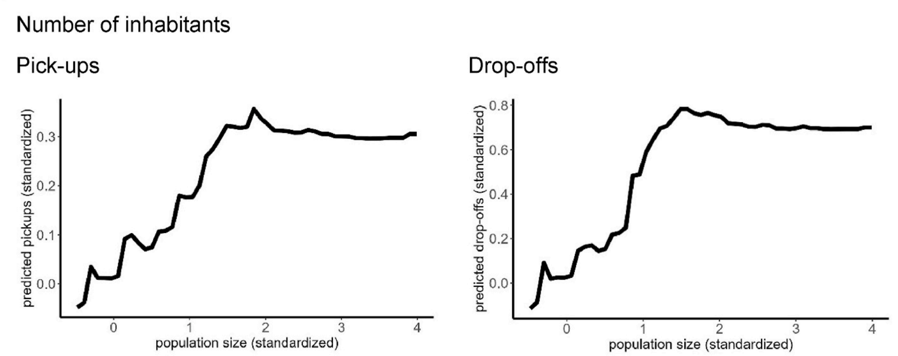


**Fig. 5.** Partial dependence plot for the variable "population size".

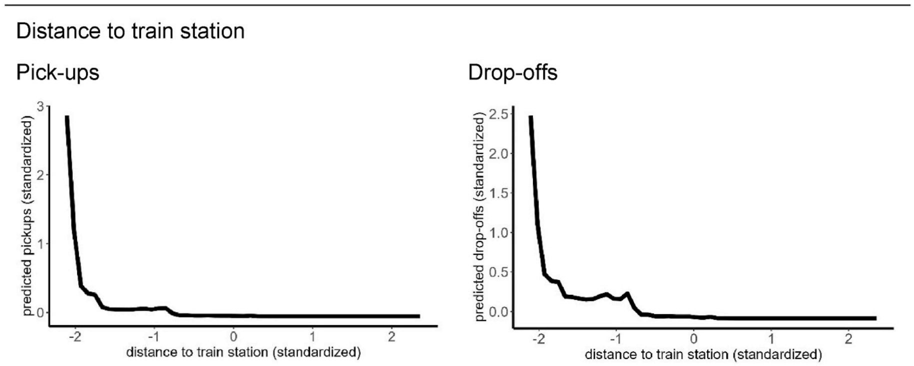


**Fig. 6.** Partial dependence plot for the variable "distance to train".

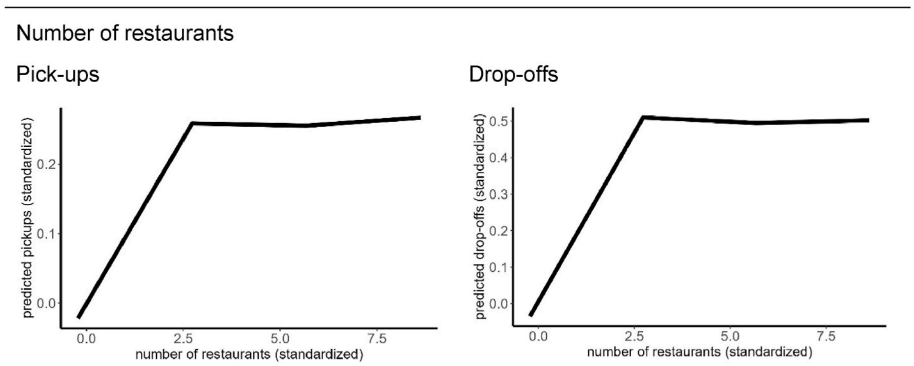


**Fig. 7.** Partial dependence plot for the variable "number of restaurants".

## CRediT authorship contribution statement

**Sebastian Imhof:** Supervision, Conceptualization, Formal analysis, Resources, Visualization, Writing – original draft, Writing – review & editing. **Kevin Blättler:** Conceptualization, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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