**University of
Zurich**^{UZH}

**Zurich Open Repository and
Archive**

University of Zurich
University Library
Strickhofstrasse 39
CH-8057 Zurich
www.zora.uzh.ch

Year: 2020

Dialect borders - political regions are better predictors than economy or religion

Derungs, Curdin ; Sieber, Christian ; Glaser, Elvira ; Weibel, Robert

Abstract: The impact of geography on language and dialect variation has been subject to a vast number of studies in linguistics, as well as the broader humanities. Most quantitative research concerning dialectology has focused on the relationship between spatial distance and change of dialects. Hypotheses regarding the impact of other geographic, cultural, and social factors have been put forth for many years but have rarely been examined with quantitative methods. In this article, we compare dialect variation in Swiss German morphosyntax with three types of social and cultural variation, namely variation in religion, administration, and economy. These different types of variation have contrasting temporal origins. Religion is, for instance, represented by the borders between Christian denominations, which are a result of the Reformation in the 16th century. In order to compare different types of spatial information in one statistical model, we introduce an approach that is robust for spatial dependencies. On one hand, our results are largely in agreement with previous studies. Spatial distance, for instance, proves to be the most important predictor of dialect variance, with distance measures that more realistically represent the potential for social contact, explaining a higher proportion of variance. On the other hand, most interestingly, we find evidence that administrative borders (i.e. political regions) more profoundly impact Swiss dialects than religion or economy. This opens the floor for the hypothesis that possibly both Swiss dialects and political regions have common origins in ancient migration movements and medieval borders between Alemannic territories.

DOI: <https://doi.org/10.1093/llc/fqz037>

Posted at the Zurich Open Repository and Archive, University of Zurich

ZORA URL: <https://doi.org/10.5167/uzh-178935>

Journal Article

Published Version

Originally published at:

Derungs, Curdin; Sieber, Christian; Glaser, Elvira; Weibel, Robert (2020). Dialect borders - political regions are better predictors than economy or religion. *Digital Scholarship in the Humanities*, 35(2):276-295.

DOI: <https://doi.org/10.1093/llc/fqz037>

Dialect borders—political regions are better predictors than economy or religion

Curdin Derungs

University of Zurich, Zurich, Switzerland; Lucerne University of Applied Sciences and Arts, Institute of Building Technology and Energy, Luzern, Switzerland; and Department of Geography, University of Zurich, Winterthurerstrasse 190, Zurich, Switzerland

Christian Sieber

Office of Land Registry and Geoinformation, Department of Geoinformation, Canton of Zug, Zug, Switzerland

Elvira Glaser

German Department, University of Zurich, Zurich, Switzerland and University of Zurich, University Research Priority Program Language and Space, Zurich, Switzerland

Robert Weibel

Department of Geography, University of Zurich, Zurich, Switzerland and University of Zurich, University Research Priority Program Language and Space, Zurich, Switzerland

Abstract

The impact of geography on language and dialect variation has been subject to a vast number of studies in linguistics, as well as the broader humanities. Most quantitative research concerning dialectology has focused on the relationship between spatial distance and change of dialects. Hypotheses regarding the impact of other geographic, cultural, and social factors have been put forth for many years but have rarely been examined with quantitative methods. In this article, we compare dialect variation in Swiss German morphosyntax with three types of social and cultural variation, namely variation in religion, administration, and economy. These different types of variation have contrasting temporal origins. Religion is, for instance, represented by the borders between Christian denominations, which are a result of the Reformation in the 16th century. In order to compare different types of spatial information in one statistical model, we introduce an approach that is robust for spatial dependencies. On one hand, our results are largely in agreement with previous studies. Spatial distance, for instance, proves to be the most important predictor of dialect variance, with distance measures that more realistically represent the potential for social

Correspondence:

Robert Weibel, Department of Geography, University of Zurich, Winterthurerstrasse 190, Zurich 8057, Switzerland.

E-mail:

robert.weibel@geo.uzh.ch

contact, explaining a higher proportion of variance. On the other hand, most interestingly, we find evidence that administrative borders (i.e. political regions) more profoundly impact Swiss dialects than religion or economy. This opens the floor for the hypothesis that possibly both Swiss dialects and political regions have common origins in ancient migration movements and medieval borders between Alemannic territories.

1 Introduction

Charles de Gaulle once famously complained ‘How can one govern a country that has 246 different kinds of cheese?’ (found in Sherrin 2008). Only recently, a Swiss federal minister¹ put de Gaulles’ preoccupation for cheese into context by arguing that Switzerland, although 15 times smaller in size, has more than 450 kinds of cheese. What both politicians refer to, when counting cheese varieties, is spatial heterogeneity or variation. Switzerland’s jurisdiction, for instance, varies depending on the granularity of some 2,000 local municipalities and, fundamentally, across its 26 cantons. On a relatively small spatial extent, a variety of different economic systems prevail, ranging from agricultural production and tourism in rural areas, to information and service societies in urban Switzerland. The Reformation led to a segregation of Switzerland into a complex spatial pattern of different Christian denominations. Finally, Switzerland counts four official languages, with Swiss German being spoken in ‘one of the liveliest dialect areas in central Europe’ (Scherrer and Stoeckle, 2016, p. 32).

The aim of this study is to compare administrative, religious, and economic variation with the variation of Swiss German dialects at the syntactic level (with syntax denoting the rules and principles governing the structure of sentences). Comparing social and cultural configurations to the distribution of dialects, and vice versa, has long been a contested topic in dialectology and the cultural sciences (e.g. Chambers and Trudgill, 1998). However, it has also early been acknowledged that the present distribution of dialects might bear information on the history and evolution of present-day societies (Frings, 1948). Efforts to unravel such information through quantitative analysis are largely missing in dialectology to date. This is surprising, given the recent

considerable increase of corresponding studies in other linguistic fields (e.g. Bouckaert *et al.*, 2012; Grollemund *et al.*, 2015).

Information on dialect variation is retrieved from an extensive linguistic atlas project on Swiss German syntax, namely the SADS² (Bucheli and Glaser, 2002; Glaser and Bart, 2015). The study design is associated with a series of theoretical and methodological challenges, which will be introduced in the following sections. The methodology used in this article is sufficiently generic so as to be transferred to dialects other than Swiss German and to linguistic levels other than syntax.

2 Background

2.1 Distance, social contact, and borders

One of the earliest and most famous empirical accounts of the impact of geographic space on language is a study by Séguy (1971), in which he compared spatial distance and lexical difference between dialects and showed that linguistic variation increases with increasing distance, following a logarithmic function. Later, Nerbonne (2010) called this correlation, which was replicated in various studies, ‘Séguy’s curve’. This curve resembles the shape of a semivariogram function, which is one of the most prominent frameworks for quantifying spatial dependence in statistics (Stein, 2012).

From a more theoretical perspective, spatial distance is conceptualized as an inhibitor (if large) or facilitator (if small) of social contact and communication, as verbal interaction is more likely to occur between speakers that are not separated by large spatial distances. Bloomfield (1933) developed the concept of the ‘density of communication’ to denote the amount of verbal interaction among individual members of a community, whereby low densities of communication would foster linguistic

differences and diversity. Along this line of thought, it has been shown that measures of spatial distance that represent the potential for contact via more realistic means, such as travel time (*TT*) (e.g. Gooskens, 2004; Jeszenszky *et al.*, 2017) or the incorporation of vertical distances (Nichols, 2013), are more representative of linguistic variation.

Not long after Séguy's seminal study, Trudgill (1974) introduced the 'gravity model' for languages and thus added a second factor for estimating the influence of one location on another, namely population size. The gravity model suggests that linguistic change is not merely a spatial process that follows the path of least spatial effort; linguistic innovation might often leap from one densely populated place to another. Rural areas in the in-between may remain unaffected. Nerbonne and Heeringa (2007) subjected the gravity theory to an empirical reality check and found that spatial distance should be considered the more influential factor, compared to population size. A comparable insight was gained in a follow-up study where a series of other social variables were added to the equation (Wieling *et al.*, 2011). Compared to a series of socio-demographic variables, such as income, age, or gender structure, geographic distance still proved to be the most valuable predictor of linguistic variation.

Here, we will follow Trudgill's example. Linguistic innovation should be conceptualized as a function of social contact, rather than exclusively a function of distance. However, instead of using current socio-demographic information, we will evaluate the impact of different types of historical borders on dialect variation in Switzerland. Religious, economic, and administrative borders have their origins in different centuries and represent profound structures of Swiss society. The Reformation in the 16th century, for instance, is considered one of the most formative events in Swiss history, with families, villages, and regions divided into different denominations (e.g. Holenstein, 2009).

There exist early theoretical considerations regarding the impact of extralinguistic borders on dialects. These considerations suggest, for instance, that dialect borders could represent archaic tribal territories or that parishes played a formative role

(Bandle, 1997; Niebaum and Macha, 2006). Frings adopted the term *Kulturmorphologie* (Grober-Glück, 1982) and claimed that respective accounts might be promising for gaining insights on historical constellations, population history, and the social role of language (Frings, 1948). These accounts, however, no matter whether focusing on historical settlements or cultural elements (Knobloch, 2010) were later criticized by structural linguists (cf. Jongen, 1982; Bandle, 1997; Haas, 2010), which might be the reason for the surprising lack of more recent, quantitative investigations on borders and language. The exceptions include a continuing interest in the impact of national borders (e.g. Kremer, 1984; de Vriend *et al.*, 2008; Woolhiser, 2005; Woolhiser, 2011) and, more relevant for our line of research, an investigation by Valls *et al.* (2013). These authors explored the impact of borders on dialect variation and evolution on the example of two administrative units, Aragon and Catalonia in Spain. The article concludes with the remark that it 'might also be very interesting to relate all these processes to other socio linguistic variables' (p. 139), which is an additional motivation for exploring the impact of several types of borders on dialects.

2.2 Incorporating spatial dependence

Spatial statistics in dialectology to date was often confined to merely representing the results of classical, non-spatial statistical analysis on maps. The underlying analysis thus often ignores the spatial nature of the input data. Examples include unsupervised clustering (Wieling *et al.*, 2013; Scherrer and Stoeckle, 2016), principal component analysis (Hyvönen *et al.*, 2007; Pröll *et al.*, 2014), multidimensional scaling (Nerbonne, 2009), and regression analysis (Jeszenszky *et al.*, 2017). There are exceptions to this rule with, for instance, Wieling *et al.* (2011) using generalized additive models and splines to fit spatial trend surfaces.

The linguistic input data used with all of the above-mentioned approaches were collected in geographic space (i.e. is associated with spatial locations). They must therefore be expected to contain spatial dependencies, also known as spatial autocorrelation. This effect is, for instance, implied by the term 'dialect continuum' (Heeringa and Nerbonne,

2001) but has only rarely been considered explicitly in quantitative studies in dialectology, such as by Grieve *et al.* (2011). Spatial dependencies fundamentally bias the outcome of a statistical analysis if not explicitly accounted for (Legendre, 1993). At a later point in this article, we will elaborate on a solution for spatial dependencies in the present case study. At this point, it is important to note that ignoring spatial dependencies in statistical analysis usually leads to incorrect test statistics (Anselin and Rey, 1991). In the case of positive spatial autocorrelation, confidence intervals are underestimated, and thus the risk of type I errors increases (i.e. false rejection of the null hypothesis).

2.3 Syntax in German-speaking Switzerland

We would like to conclude this section by focusing on two questions: ‘Why syntax?’ and ‘Why Swiss German?’ Answering the latter question is simple. As illustrated by the considerable diversity in cheese, Switzerland is a linguistically, culturally, administratively, and topographically diverse country, and the German-speaking part is famous for its high degree of dialect variation and vitality of its dialects (Bickel and Schläpfer, 2000). It is thus an ideal testbed for exploring the impact of social and cultural contact on dialect variation.

Regarding the former question, distributional patterns in syntax have received relatively little scientific attention in dialectological research, particularly when compared to phonology or lexicon. In the past, it has been argued, for instance, that syntax does not constitute predictable spatial distributions (Löffler, 2003). Recent research, however, found that syntax features constitute dialect areas of sometimes large spatial extent (Scherrer and Stoeckle, 2016). The latter finding is supported by the more theoretical notion that grammar—which syntax is part of—should be considered relatively robust for short-term variation and thus represents linguistic signals of profound temporal depth (e.g. Sankoff, 2002). Robustness for spatio-temporal variation is a welcome characteristic for this investigation, where dialect variation is compared to social and cultural variation dating back to different eras. Our study can, thus, also contribute to our

knowledge about the stability and change of syntactic areas, whereas the behaviour of phonology and lexis has formed the focus of earlier work. It is well known at least for the lexicon that it can change quickly, for instance, depending on cultural trends.

3 Materials and Methods

The statistical comparison between dialect variation, spatial distance measures, and different types of borders requires the following types of input information:

- (1) a measure of dialect variation;
- (2) measures of spatial distances between pairs of locations in Switzerland; and
- (3) different types of borders in a digital, georeferenced format.

The derivation of this information will be described in the following sections. As a final methodological step, the statistical analysis will be discussed in detail.

3.1 Dialect variance

The approach to measuring dialect variance between pairs of locations in German-speaking Switzerland, as used in this study, was first introduced by Jeszenszky *et al.* (2017). Dialect information for individual locations is retrieved from the Syntactic Atlas of Switzerland (i.e. SADS; Bucheli and Glaser, 2002; Glaser and Bart, 2015). In this study, syntax information for some sixty morphosyntactic variables is incorporated.³ The variables were manually selected from a list of more than 100 variables contained in the SADS database, with the aim of exhaustively representing syntactic richness, while avoiding the introduction of collinearity. The variables were sampled at 383 Swiss German municipalities, representing approximately one quarter of German-speaking municipalities in Switzerland (Fig. 1). For each municipality, the answers of some 3–25 respondents are incorporated (median = 6). All linguistic variables are coded on a categorical scale, often of binary nature. The multiple responses per municipality make it possible to aggregate responses to relative frequency distributions (e.g. in municipality *i*, 90% of all respondents

Fig. 1 The distribution of the 383 municipalities sampled in the SADS data set and incorporated into this study. The German speaking part of Switzerland is highlighted in a light shade of grey.

showed preference for variant K_1 over variant K_2 , of variable A).

Spruit (2006) computed dialect variance in syntax data using the Hamming distance, while Spruit *et al.* (2009) used Goebel's (1984) *gewichteter Intensitätswert* (GIW), originally introduced for lexical data. Since in the SADS, multiple responses exist per survey site and thus multiple variants may co-occur per site, in our case, syntax variance is measured as the sum of relative frequency differences over all variants of all sixty morphosyntactic variables. A detailed description and evaluation of this measure, including references to further, similar measures is given in Jeszenszky *et al.* (2017). A value of syntax variance is calculated for each pair of the 383 municipalities included in the SADS ($n = \frac{383 \times (383-1)}{2} \approx 70k$).

3.2 Spatial distance measures

We incorporate three measures of spatial distances between SADS municipalities in this study. Spatial distance is used as a measure of accessibility, which in turn represents the potential for social contact (e.g. Trudgill, 1974). More realistic measures of accessibility [e.g. *TT*, when compared with Euclidean distance (*ED*)] should therefore be better predictors of linguistic variation. This has been shown in numerous studies (e.g. Nerbonne, 2010; Szmrecsanyi, 2012).

Three distance measures are compared in this study:

- *ED* is the shortest distance between two locations on a plane.
- Hiking time (*HT*) is estimated by incorporating the Earth's topography and is computed as the estimated time required for hiking the path of least topographic effort between two locations (i.e. least cost path, LCP: Douglas, 1994). Only the 'naked' topography is considered, and lakes are represented as level surfaces, posing no resistance to movement.
- *TT* is the time required to travel from one location to another by car, using the transportation network and all available infrastructure from around the year 1950. *TT* estimates from the 1950s are favoured over more recent estimates, since the former represent the state of the Swiss road network before the comprehensive national highway network was established. *TT* measures were computed and provided by transportation researchers (Fröhlich *et al.*, 2004) and have previously been shown to highly correlate with syntax variation in Switzerland (Jeszenszky *et al.*, 2017).

Of the three distance measures, it may be argued that *HT* is the best in terms of applicability in other language studies. *HT* is better suited to the task of coherently representing accessibility than *ED* is. At the same time, *HT* is more generic than *TT*. The only requirement for computing *HT* for a set of locations is a digital elevation model (DEM). DEMs are openly available for global extents with 90 m spatial resolution (Jarvis *et al.*, 2008). In this study, we use an elevation model provided by the Swiss federal mapping agency (Swisstopo), namely DHM25⁴ with 25 m resolution. *HT* is computed by associating each grid cell of the digital elevation model with a cost, representing the time required for traversing the respective cell. The time requirement is a function of the local slope, with steep positive slopes requiring more time to ascent when compared with, for instance, more planar slopes. The translation of slopes into time-costs is performed using Tobler's hiking function (Tobler, 1993). The resulting cost surface is queried using the

Dijkstra-Algorithm (Skiena, 1990), such that for each pair of municipalities in our dataset, a minimum *HT* is computed. The computation of *HT* is performed using the R-package *gdistance* (van Etten, 2017).

3.3 Spatial borders

We incorporate three types of borders into this study, namely religious, administrative, and economic borders (Fig. 2).

Religious borders differentiate between Christian denominations in Switzerland (i.e. Roman Catholics and Protestants, Fig. 2B). The Reformation in the 16th century is considered one of the most formative processes in Swiss history (e.g. Holenstein, 2009), and hence it is interesting to compare this to the distribution of Swiss dialects. The spatial distribution of denominations in Switzerland is digitized and georeferenced from a cartographic representation contained in the *Sprachatlas der Deutschen Schweiz* (Hotzenköcherle *et al.*, 1962).

Secondly, borders of the 26 Swiss cantons are used as an example of administrative borders (Fig. 2A). In the Swiss Federation, cantons have independent constitutions and legislature and therefore represent an important structuring element of Swiss society. We use the polygon dataset made available by the Federal Statistical Office.⁵

Finally, the borders between Swiss metropolitan areas are used as an example of economic borders (Fig. 2C). Recent work by Lameli *et al.* (2015) has illustrated that dialect areas might impact the intensity of trade. The metropolitan areas are provided by the Swiss Federal Statistical Office and are based on

the commuting behaviour, as measured in the 1960s.⁶

All pairs of municipalities in our dataset are intersected with all three types of borders for the follow-up statistical comparison. We test both municipalities in terms of whether they are located in the same religious area, the same canton, or the same metropolitan region. The results are three Boolean vectors, one for each type of border. The value 0 indicates that both municipalities are in the same region, and 1 indicates that travelling from one municipality to the other requires the crossing of a border.

Since segments of the different borders often overlap—e.g. a religious border might often also be a cantonal border—we compute one additional vector. This vector is multinomial and contains a category for all eight possible combinations of borders (e.g. ‘no border’, ‘only cantonal’, ‘cantonal and economic’, ‘all borders’).

3.4 Unbiased spatial regression

The three types of input information are combined into one modelling framework of the following general form:

$$\text{dialect Variance} \sim \text{spatial Distance} * \text{border} + \text{error}$$

Dialect variance and spatial distance measures are log-transformed and scaled ($v_i^* = \frac{v_i - \mu}{\sigma}$) in order to account for skewness and to foster comparability between different models. The multiplication sign between the explanatory variables (*) implies that we test for both the constant impact of borders on

Fig. 2 The three different types of borders incorporated into this study. The German speaking part of Switzerland is highlighted in a light shade of grey in all three maps.

Table 1 Regression models used in this study. The first column gives the abbreviations used in the remainder of the article

Abbrev.	Full equations
~ED	$dialectVariance_i = B_0 + B_1 * ED_i + E_i$
~TT	$dialectVariance_i = B_0 + B_1 * TT_i + E_i$
~HT	$dialectVariance_i = B_0 + B_1 * HT_i + E_i$
~HT*cant	$dialectVariance_i = B_0 + (B_1 * HT_i) + (B_2 * cant0_i) + (B_3 * cant1_i) + (B_4 * cant0_i * HT_i) + (B_5 * cant1_i * HT_i) + E_i$
~HT*relig	$dialectVariance_i = B_0 + (B_1 * HT_i) + (B_2 * relig0_i) + (B_3 * relig1_i) + (B_4 * relig0_i * HT_i) + (B_5 * relig1_i * HT_i) + E_i$
~HT*econ	$dialectVariance_i = B_0 + (B_1 * HT_i) + (B_2 * econ0_i) + (B_3 * econ1_i) + (B_4 * econ0_i * HT_i) + (B_5 * econ1_i * HT_i) + E_i$
~HT*bord	$dialectVariance_i = B_0 + (B_1 * HT_i) + (B_2 * cant1_i) + \dots + (B_n * cant1_i * relig1_i) + \dots + (B_m * cant1_i * relig1_i * econ1_i * HT_i) + \dots + E_i$

dialect variance (intercept) and the interaction between borders and spatial distance (slope). In order to compare the different distance measures, as well as the different types of borders, the models shown in Table 1 are tested separately.

Models that only contain one type of border incorporate a Boolean variable, with *cant1* being 1 if a cantonal border is crossed and 0 otherwise; *cant0* contains the inverse encoding. The model that incorporates all types of borders (~HT*bord) incorporates a multinomial variable with eight classes. Its equation is therefore more comprehensive. In order to compare the performance of the three models containing distance measures, R^2 -values are used, representing the proportion of explained variance. Models incorporating borders are compared using standard analysis of variance for nested models, comparing each model to the baseline model (~HT).

The above regression model must be extended in two ways, in order to deal with violations of the assumption of independently sampled input data. Both extensions are motivated by types of dependencies that typically occur in pairwise comparisons of spatial data (Fig. 3).

The first type of dependency is usually termed a population effect and occurs if pairwise comparisons share a sample location (in our case, a municipality). In Fig. 3A, comparisons a and b both share one municipality. The dialect particularities of this municipality impact both pairwise comparisons a and b. If the municipality happens to be an outlier, for linguistic or non-linguistic reasons (e.g. error in data recording), its bias is propagated to both

comparisons. If all possible combinations of municipalities are incorporated into one model (which is usually done in dialect studies), one outlier might impact $n - 1$ pairwise comparisons, where n is the total number of municipalities.

There exist statistical frameworks, developed in ecology, that make it possible to incorporate population effects in the correlation structure of regression models (Clarke *et al.*, 2002). However, these models have never been extended to also capture other types of dependencies. We therefore use a less formal, alternative approach based on a subsampling procedure. More specifically, we subsample unbiased datasets from all pairwise comparisons. Subsamples are unbiased if no municipality is allowed to occur more than once in one subsampled input dataset (e.g. the pairs a and b would not occur together in one subsample). This can only be guaranteed if only some 191 of all 70,000 comparisons are selected in each subsampling iteration. The 383 municipalities constitute $\frac{383!}{2}$ unique subsamples; of these, we test a random subset that comprises 500.

The second type of dependency is spatial in nature. Pairwise comparisons proximate in geographic space (e.g. b and c, Fig. 3A) are expected to have more similar dialect variation, especially compared to distant comparisons (e.g. c and d). Such spatial autocorrelation introduces a bias to the statistical analysis. The number of observations in the input data (in our case, the 191 pairwise municipality comparisons) is considerably larger than the number of independent observations. This leads to an overestimation of the degrees of freedom,

Fig. 3 Sketch of the two types of dependencies present in the pairwise distance and dialect comparisons used in this study. (A) Comparisons a and b are dependent, since they both share one common node (i.e. a municipality). (B) Comparisons b and c are prone to spatial dependence, since they are, for instance, more proximate than c and d.

which in turn results in an underestimation of confidence intervals and thus introduces the risk of falsely rejecting the null hypothesis (Type I error).

We use spatial autoregressive models in order to capture the bias of spatial autocorrelation (e.g. Anselin, 2002). The spatial correlation structure of the input data is explicitly incorporated into the error estimation, with spatially proximate observations gaining higher weight in the model optimization. The spatial correlation structure is computed from the distances between pairs of comparisons, i.e. the distance between the midpoints of each pair of municipalities (Fig. 3B). The impact of spatial autocorrelation on the model's performance can be estimated, which makes it possible to explicitly evaluate whether the incorporation of the spatial correlation structure is of importance. We use the *R*-function `errorsarlm()` from the *spdep* package (Bivand *et al.*, 2019) in order to compute spatial autoregressive models.

Importantly, the impact of spatial borders on our regression model could be an artefact of spatial clustering. Cantonal borders, as an example, cluster communities that are proximate in geographic space into groups (i.e. all communities that lie within the same canton). Adding such spatial groupings to a regression model might help to explain spatial variation, without actually adding useful information. In order to test for this artefact,

we run some fifteen iterations of all the above spatial regression models, however, using random tessellations of Switzerland. Each random tessellation mimics cantonal, religious, and economic borders. For the example of cantons, Switzerland is, for instance, divided into twenty-six randomly delineated regions. Results obtained from original and random border tessellations can then be compared.

4 Results and Interpretation

First, we present the results of the simple spatial regression models and compare dialect variance to spatial distances. The performances of the different distance measures are compared, and one measure is selected and used in all follow-up analyses. Secondly, the impact of borders on dialect variance is evaluated, without and with the incorporation of distance measures.

4.1 Simple spatial regression model

Figure 4 visualizes the relation between dialect variation and one of the three distance measures, i.e. *HT*. The grid cells in the background represent the input data in an aggregated form. The 70k pairwise comparisons between the 383 municipalities are summarized and counted for each cell. Bright colours indicate high counts. The black lines show

Fig. 4 Scatterplot of dialect variance and HT for all pairwise comparisons of the 383 municipalities in the SADS data set. Axes are log-transformed and scaled. Individual observations are aggregated to counts as honey-combs, with bright shades indicating a large number of observations. The black lines represent 100 (of the total of 500) regression lines. Both axes are log-transformed and normalized.

some 100 randomly selected regression lines, from the total of 500 models, fitted on unbiased subsamples of the original data.

Two observations can be made when looking at Fig. 4:

- The direction of the dependency between dialect variance and *HT* (and spatial distances in general) is positive. If *HT* between two municipalities is long, the two municipalities have diverse dialects.
- Regression models fitted to different unbiased subsamples of the original data show a certain degree of variation.
- The uneven distribution of dialect variation and *HT* values, with most input data being mapped to the centre of the plot (bright grid cells), exerts an impact on model fits. The variation between the fitted regression lines is smallest where most data are available.

Figure 5 presents boxplots for the 500 subsampled models, with dialect variance as the target and spatial distance as the explanatory variable. Results are represented for models incorporating

$\sim ED$, $\sim TT$, and $\sim HT$ as distance measures. The simple intercept model ($\sim I$) is added for comparison purposes. The plot to the left shows R^2 values (i.e. explained variance). The plot to the right shows the distribution of the b_1 coefficients (i.e. model slopes).

We would like to highlight the following observations:

- The intercept model ($\sim I$), only consisting of a global mean, explains considerably less variance (low R^2) when compared to the spatial distance models. Hence, spatial distance should be considered an important predictor of dialect variance.
- The three models containing spatial distance measures (i.e. $\sim ED$, $\sim TT$, and $\sim HT$) all have high predictive power, with a median of 55–60% of dialect variance being explained (cf. median R^2 values as added to Fig.5, left).
- TT explains more variance in comparison to HT , which in turn explains more variance than simple ED . All three spatial measures explain a significant proportion of the variance of R^2 values (P (F -value) < 0.05), and confidence

- Subsampling triggers within-model variation, represented by the extent of the boxplots. The degree of variation is comparable across all models and does not significantly impede model comparison.
- Model slopes (beta coefficients; Fig. 5, right) are related to the R^2 values. *TT*, which explains most of the variance, also shows the steepest slope.

2016). This might be related to the impression of continuous change over space, as visualized in Fig. 6, and perhaps an arguable association with what has been termed a dialect continuum in other contexts (Heeringa and Nerbonne, 2001).

The map of positive residuals in Fig. 6B shows high values in the (sub)alpine regions of central Switzerland, but we can also see that clusters of positive residual values often overlap with Swiss cantonal borders. Examples include the borders between Berne and Valais, Fribourg and Berne, or Zurich and Schwyz, respectively. Since positive residuals mean higher than expected linguistic differences and they tend to cluster in the vicinity of cantonal borders, we hypothesize that these borders may have an impact on the spatial distribution of dialects. We will therefore place a major focus on the impact of borders on Swiss dialects.

In the following experiment, the impact of borders on dialect variance is tested without the incorporation of spatial distance. Figure 7 shows the density distributions (i.e. smoothed histograms) of dialect variance. Each of the seven plots contains two density distributions. The light grey density distribution represents dialect variance if no border is crossed. This is the same in all plots. Additionally, each plot contains the distribution of dialect variance if one

Fig. 6 Spatial representation of residual values of the model with *HT*. Negative (A) and positive (B) residual values are plotted in separate maps. Negative residuals indicate an over-estimation of dialect variance, given the distance between municipalities, and vice versa. Individual residuals are conceptualized as lines, connecting two municipalities, and aggregated to line-density maps for better interpretation. Dark shades indicate a large number of high absolute residual values at the respective location. Swiss cantonal borders are plotted on top of the residual maps. The German speaking part of Switzerland is highlighted in the background.

border, or a combination of borders, is crossed (dark grey plots).

Figure 7 allows making the following observations:

- Most salient differences between the border-crossed (dark grey) and the no-border-crossed (light grey) density distributions are observed for comparisons that incorporate cantonal borders. The three comparisons with cantonal

borders (i.e. *Cant.*, *Cant. & Relig.*, *Cant. & Econ.*, and *all bord. crossed*) all show a similar pattern. The border-crossed curve is shifted to the right, towards larger values of dialect variance. Crossing a cantonal border leads to higher dialect variance when compared to not crossing a cantonal border (i.e. not crossing any border or a combination of borders not incorporating cantonal borders).

- The numbers in each plot represent the percentage of times the hypothesis of similar distribution of the two density distributions is rejected across all 500 unbiased subsamples (one-sided Mann–Whitney U test). Crossing a cantonal and economic border, or a combination of all borders, leads to a significant increase in dialect variance in (almost) 100% of the cases.

It is important to note that the comparison in Fig. 7 might be confounded by spatial distance. The probability of crossing a border clearly increases if two municipalities are located far from one another.

In order to disentangle the impact of borders and distances, we combine both measures in one statistical framework. In the following, we use *HT* as a measure of spatial distance. *HT* was outperformed by *TT* in the previous comparison (c.f. Fig. 5). However, as argued earlier in this article, *HT* offers a compromise between simplicity (ED) and overly complex and particular computation (*TT*).

Figure 8 presents a comparison of the five models. The model with dialect variance as the target variable and *HT* as the only predictor ($\sim HT$) serves as a baseline (no border is incorporated). The other four models each use *HT* in combination with one type of border. Cantonal ($\sim HT^{*cant}$), religious ($\sim HT^{*relig}$), and economic ($\sim HT^{*econ}$) borders are first incorporated separately (each as a binary variable, cf. Materials and Methods). Finally, the combination of all borders is tested ($\sim HT^{*allBord}$).

We represent the percentage of times the models with borders perform significantly better than the model without borders ($\sim HT$) across all 500 subsamples. Statistical significance is tested with an analysis of variance of the nested models; the $\sim HT$ model is nested in all border models.

Fig. 7 Density plots of dialect variance without (light grey) and with (dark grey) crossing of a border between municipalities. Each combination of the three types of borders, cantonal (Cant.), religious (Relig.) and economic (Econ.), is separately plotted against the no-border case. Numbers in each plot represent how often in all 500 unbiased subsamples the hypothesis of similar distribution has been rejected (one-sided Mann–Whitney U with $P < 0.05$).

Fig. 8 (A) pseudo R^2 values of the baseline ~HT model, and all four models that contain borders. (B) Statistical comparison between border models and the ~HT model. The percentage of times the border models perform significantly better than the ~HT model is represented.

Figure 8 gives rise to the following observations:

- The statistical comparison of the border models and the baseline suggests that the higher proportion of explained variance (Fig. 8A) often fails to compensate for the increased model complexity (Fig. 8B). From all four border models, only two models outperform the baseline (~HT) in more than 50% of the tests (black horizontal line in Fig. 8B).
- Religion (~HT*relig) and economic (~HT*econ) borders improve the baseline model in less than 50% of the cases. This is below the random odds.
- The two models incorporating cantonal borders (~HT*cant) and all borders (~HT*allBord), both outperform the baseline model in more than 50% of the cases (Fig. 8B). From these two models, the all-border model shows higher pseudo R^2 values (0.63 versus 0.57) and a higher percentage of times outperforming the baseline (62% versus 58% improvement).

In order to test that the impact of borders is not merely an effect of spatial grouping, but represents the impact of cantons, religion, or economy on Swiss dialects, random spatial borders were tested

using the procedure described in Section 3.4. Appendix A presents the results for fifteen random, but structurally similar (e.g. same number of groups, similar granularity), tessellations of Switzerland into fictive cantons, religious denominations, and economic regions. Results indicate that the R^2 does not increase if random spatial borders are added to the model. Additionally, models incorporating random spatial borders only rarely outperform the baseline model. The results shown in Fig. 8 should therefore not be considered as an artefact of spatial grouping or granularity. Also, Appendix A suggests that spatial grouping does have an impact on R^2 values and the outcome of performance tests. However, there is clearly a pattern that (random) cantons are better predictors than (random) economic or religious borders due to the impact of spatial granularity.

All models in this case study use spatial autoregressive models. Spatial autocorrelation is submitted to each model run as input information. Its impact on the model's performance can be statistically evaluated. Table 2 shows the percentage of times spatial autocorrelation significantly improves the model's performance over all 500 subsamples ($\lambda P < 0.05$).

Spatial autocorrelation proves to have a significant impact on (almost) 100% of the model runs. This pattern can be observed across all models. The incorporation of spatial autocorrelation is crucial when it comes to comparing dialect variance to spatial distances and other spatial predictors. Ignoring spatial autocorrelation leads to biased results, which raises some questions as to the validity of results published in the majority of previous studies.

5 Discussion

We argue that dialect variation has been explored from various perspectives. There is general agreement that spatial distance is a measure of accessibility,

which in turn is an important driver for social contact and thus facilitates linguistic innovations (Trudgill, 1974). Given the wealth of studies concerning areal linguistics, it is surprising, however, that borders have rarely been incorporated as indicators of social and cultural variation. In this study, we therefore set out to quantify the impact of historical, social, and cultural borders on dialect variation. This undertaking gains additional support from preliminary results in this study, represented in Fig. 6. Simple distance models have the highest proportion of unexplained dialect variance in border regions. In the following, separate discussions are put forth regarding major insights into the use of spatial distance measures, the impact of different types of borders, and methodological constraints.

5.1 Spatial distance measures

From the literature, there arise three hypotheses pertaining to the impact of spatial distance measures:

- First, distance measures are found to explain a higher proportion of variance compared to social factors (Heeringa and Nerbonne, 2001; Wieling *et al.*, 2011).
- Secondly, distances are used as a measure of the degree of social contact or the 'density of communication' (Bloomfield, 1933). Distance measures representing the probability of social contact in more realistic ways are therefore hypothesized to explain a higher proportion of dialect variance (Nerbonne, 2010).
- Thirdly, the observed pattern of dialect distribution is a product of spatio-temporal diffusion processes that have worked for centuries (e.g. Chambers and Trudgill, 1998). Distance measures that are representative of social contact over long time spans are therefore expected to better predict dialect distribution (Gooskens, 2004; Jeszenszky *et al.*, 2017).

Table 2 Percentage of autoregressive models with significant contribution of spatial autocorrelation

Model	$\sim I$	$\sim ED$	$\sim TT$	$\sim HT$	$\sim HT^{*cant}$	$\sim HT^{*relig}$	$\sim HT^{*econ}$	$\sim HT^{*allBord}$
Percentage sign. sp. autocorr.	100	100	97	99	99	98	99	99

Appendix A — Random spatial borders.

Our findings support the first two hypotheses, but not the third. As for the first hypothesis, Fig. 5 shows that the explanatory power increases by some 30–40% if spatial distance is added as a predictor to the pure intercept model (~ 1). Figure 8A indicates that *HT* alone makes it possible to explain in median 57% of the variance, while a combination of *HT* and all types of borders only explains 5% more. As such, the major contribution is clearly made by the spatial distance measure when compared to the social and cultural factors.

In accordance with the second hypothesis, we can show that *ED* explains less variance when compared to the two other measures (*HT* and *TT*, Fig. 5), with the difference in performance between the three measures being statistically significant. Most variance is explained by the measure which we described as being most ‘realistic’ for approximating social contact (*TT*). This finding is also in agreement with previous research concerning the impact of topography on language distribution (e.g. Mace and Pagel, 1995). *HT* can only be a better predictor than *ED* in situations where topography significantly impacts the distributional patterns in dialects.

The third hypothesis would suggest that *HT* explains more variance than *TT* from the 1950s. The time required to hike from one location to another (i.e. *HT*) should be considered more representative of spatial mobility in the past when compared to using a car in the 1950s (*TT*). However, we find that *HT* explains considerably less variance compared to *TT* (Fig. 5). One reason for this may be that *HT* is a very rough estimate of the actual *HT*. For instance, we ignore the impact of past travel or trade routes or different types of impeding land cover or natural barriers, such as dense vegetation, water bodies, and glaciers. *HT* in our case is solely determined by topography and many unrealistic ‘shortest’ hiking paths might result. One reason why we would still promote the use of least cost estimates over more complex and specific measures is flexibility, and ease of transfer to other study areas, where historical *TT* information may not be available. In future studies, the above-mentioned factors could be integrated into the computation of least cost paths and thus be systematically

evaluated in terms of their impact on dialect variance; indeed, this could lead to novel insights. Similar approaches have, for instance, been discussed in archaeology (Carballo and Pluckhahn, 2007; Siart *et al.*, 2008).

5.2 Impact of borders

The relation between social factors and dialect variation has been examined in previous studies (e.g. Wieling *et al.*, 2011). To the best of our knowledge, however, this is the first quantitative study that estimates social and cultural variation from different types of borders. One advantage of borders is that maps on historical border demarcations are widely available in paper or digital format. We incorporate economic borders that represent commuting behaviour from the 1960s; we also examine religious borders that represent the segregation of Switzerland into different Christian denominations after the 16th century (Holenstein, 2009); finally, we focus on cantonal borders that were legally defined in the course of the Congress of Vienna in 1815 but have their origins in the far-more-distant past (e.g. Vatter, 2002). There are, indeed, other quantitative studies focusing on the interrelation between cultural areas and dialect variation, such as Falck *et al.* (2012). The perspective of that interdisciplinary study is, however, different. Falck *et al.* (2012) are analysing the impact of dialect on migration within Germany, which they find to be high (cf. also Lameli, 2013, ch. 10). This is motivated by the overarching cultural area reflected in the dialect area, which is taken as evidence of the impact of extra-linguistic factors.

Our results show that administrative (i.e. political) borders have more of an impact on dialect variance in Switzerland when compared to religious and economic borders (Figs 7 and 8). On one hand, this finding deserves critical appraisal. The three border data sets only represent particular aspects and states in time of these three considerably complex topics. There are qualitative studies showing some influence of the religious denomination on dialects (e.g. Bucheli Berger and Landolt, 2014).

Nevertheless, the question ‘Why administrative borders?’ deserves additional consideration. It has been argued that the demarcations of cantonal

borders date back to medieval times (Vatter, 2002). The *Sprachatlas der deutschen Schweiz* (Hotzenköcherle and Trüb, 1962) contains a map showing the territorial subdivision from 1536 on, thus suggesting an impact of this historical delineation (cf. also Hotzenköcherle, 1962, p. 7). On the other hand, it has also been suggested that some of the dialect borders concerning mainly phonological characteristics coincide with early migration paths of West Germanic tribes in Switzerland (e.g. in Bickel and Schläpfer, 2000). If agreed upon, this theory could mean that some cantonal borders might even date back to an early era of Swiss dialect formation. However, there is only a small amount of empirical evidence in support of this tentative hypothesis. Following the prevailing theories, most of the recent dialect variation nevertheless originated in medieval times (Sonderegger, 2003) without, of course, assessing syntax. This said, studies of dialect change in the 20th century suggest that Swiss dialects only experienced relatively slow change, with relative stability in phonology, compared to lexicon (Leemann *et al.*, 2016). While no comparative studies on syntax exist, theoretical considerations would predict that syntax is more stable than phonology (e.g. Sankoff, 2002). A recent clustering analysis of different linguistic levels in Switzerland has, for instance, shown that syntax leads to larger and more coherent ‘dialect areas’ in comparison with lexicon, phonology, and morphology (Scherrer and Stoeckle, 2016).

If these pieces fit together, the present study might offer an explanation for the present Swiss dialect landscape: cantonal and dialect borders both originate from early ethnolinguistic groupings and thus still show statistically significant relations.

5.3 Methodological considerations and limitations

We introduce a methodology that makes it possible to produce unbiased computational relations between pairwise distances, border crossings and dialect variance. Our method incorporates population effects (Clarke *et al.*, 2002), as well as spatial autocorrelation (Legendre, 1993). The importance of incorporating spatial autocorrelation is shown in Table 2. In almost 100% of the model runs, spatial

autocorrelation must be incorporated in order to compute unbiased parameter estimates (Fig. 4), test statistics (Fig. 8B), and measures for model performance (Figs 5 and 8, A).

The impact of population effects is illustrated by the variation between model outputs if applied to different subsamples of the data (e.g. in Fig. 4). The variance between numerous subsampling iterations (500 in this study) makes it possible to estimate true parameter values or model performances (owing to the central limit theorem; Rosenblatt, 1956). Importantly, the unbiased method introduced in this study might also explain the differences between our results and findings in related studies.

However, the results of this study should be viewed through the prism of a series of limitations:

- Only one spatial scale of analysis is incorporated into this study, namely entire German-speaking Switzerland. On one hand, the clustering in model residuals, as visualized in Fig. 6, indicates that local patterns might require more focused analysis, for instance, in the form of a geographically weighted regression (Brunsdon *et al.*, 1998). On the other hand, the extent of Switzerland clearly introduces an artificial restriction on this study. It would therefore be interesting to incorporate larger areas of the Alemannic dialect area (extending into Liechtenstein and parts of Germany, Austria, Italy, and France) in future studies.
- We compare the current distribution of dialects with other social and cultural variability in German-speaking Switzerland and argue that this makes it possible to draw inferences regarding the evolution of both. Present social and cultural variability clearly contains a signal from the past. For instance, similar assumptions are made in recent applications of phylogenetic approaches to linguistic (e.g. Dunn, 2015) and other cultural (e.g. Mace and Holden, 2005) data. However, for an in-depth understanding of how dialects have co-evolved with other societal phenomena, more precise historical input data are required. At present, the origin of Switzerland’s rich dialect landscape is still subject to speculation.

6 Conclusion

In this article, the spatial variation in Swiss German dialects, with a focus on syntax, is related to three types of social and cultural variation, represented by borders. Switzerland is an ideal testbed for such an approach, owing to its high degree of diversity in dialects and cultural factors.

We make two major contributions: the first is related to a central finding in the article, the second is of methodological nature. Regarding the first contribution, we found that linguistic patterns in Swiss German dialects are more closely related to political (i.e. cantonal) borders, when compared with economic or religious borders. Seven decades ago, Frings posited that the evolution and thus phylogeny of a society should be reflected in its shared social, cultural, and dialect patterns (Frings, 1948). The related field in German was termed *Kulturmorphologie*, or ‘cultural morphology’. However, first case studies in *Kulturmorphologie* failed to identify larger trends and soon thereafter the correlation of linguistic characteristics with extralinguistic variables became contested (e.g. Bandle, 1997). Under the structuralist paradigm, the focus of linguistic research completely changed away from an extralinguistic explanation to an intralinguistic motivation of change (cf. Goossens, 1969). Our approach can be seen as one of few quantitative applications of Frings’ original aim, namely to explain the variance in dialects through the variance in social or cultural factors. Comparable approaches recently gained considerable attention in other fields of linguistics, such as typology (e.g. Currie and Mace, 2012) or computational linguistics (e.g. Derungs and Samardžić, 2018).

We found the highest agreement between Swiss German syntax, which is expected to be robust for arbitrary temporal variation (Sankoff, 2002), and political borders. Political borders are the extralinguistic variable with the longest temporal depth incorporated in this study in many cases going back to earlier administrative units. These findings led us to draw the following conclusion: Cantonal borders in Switzerland and Swiss dialects might have a common origin in early migration paths of

West Germanic tribes or at least in medieval territorial conditions in Switzerland (e.g. in Bickel and Schläpfer, 2000). The link to historical territorial divisions is clearly a promising hypothesis for follow-up research.

As for the methodological contribution of this article, we were able to demonstrate that the pairwise comparison of distances and variances, as is common practice in dialectology (e.g. Jeszenszky *et al.*, 2017) and other fields, such as ecology (e.g. Clarke *et al.*, 2002), requires careful incorporation of dependencies, which in turn is often omitted. We found evidence that population effects, as well as spatial autocorrelation structures both have a significant impact on the results. If ignored, these dependencies lead to biased test statistics. Therefore, the methodology presented in this article should be considered an important step towards drawing unbiased comparisons between types of variances, for instance, in linguistics, ecology, or related fields in the broader humanities and natural sciences.

Acknowledgements

We would like to thank the editor and the reviewers for their thoughtful comments, which helped to improve this article.

Funding

Funding for this work was provided by the University of Zurich Research Priority Program ‘Language and Space’ and by the Swiss National Science Foundation through grant CR12I1_162760 SynMod+.

References

- Anselin, L. (2002). Under the hood: Issues in the specification and interpretation of spatial regression models. *Agricultural Economics*, 27(3): 247–67.
- Anselin, L. and Rey, S. (1991). Properties of tests for spatial dependence in linear regression models. *Geographical Analysis*, 23(2): 112–31.

- Bandle, O.** (1997). Sprachgeschichte und Kulturgeographie in Skandinavien. In Birkmann, T., Klingenberg, H., Nübling, D. and Ronneberger-Sibold, E. (eds), *Vergleichende Germanische Philologie und Skandinavistik: Festschrift für Otmar Werner*. Tübingen: Max Niemeyer, pp. 67–79.
- Bickel, H. and Schlöpfer, R.** (eds) (2000). *Die viersprachige Schweiz*. Aarau, Frankfurt a.M., Salzburg: Sauerländer.
- Bivand, R., Altman, M., Anselin, L., et al.** (2019). spdep: Spatial dependence: weighting schemes, statistics and models. <https://cran.r-project.org/web/packages/spdep/index.html>
- Bloomfield, L.** (1933). *Language*. New York, Chicago, San Francisco and Toronto: Holt, Rinehart and Winston.
- Bouckaert, R., Lemey, P., Dunn, M., et al.** (2012). Mapping the origins and expansion of the Indo-European language family. *Science*, **337**(6097): 957–60.
- Brunsdon, C., Fotheringham, S., and Charlton, M.** (1998). Geographically weighted regression. *Journal of the Royal Statistical Society: Series D (The Statistician)*, **47**(3): 431–43.
- Bucheli, C. and Glaser, E.** (2002). The syntactic atlas of Swiss German Dialects: empirical and methodological problems. In Barbiere, S., Cornips, L., and van der Kleij, S. (eds), *Syntactic Microvariation*, Vol. 2. Amsterdam: Meertens Institute Electronic Publications in Linguistics, pp. 41–73.
- Bucheli Berger, C. and Landolt, C.** (2014). Dialekt und Konfession in der Deutschschweiz. In Friebe, E., Kanz, U., Neuber, B., Zehetner, L. (eds), *Beiträge zum 5. dialektologischen Symposium im Bayerischen Wald, Walderbach, Juni 2012*. Regensburg: edition vulpes, pp. 73–94.
- Carballo, D. M. and Pluckhahn, T.** (2007). Transportation corridors and political evolution in highland Mesoamerica: Settlement analyses incorporating GIS for northern Tlaxcala, Mexico. *Journal of Anthropological Archaeology*, **26**(4): 607–29.
- Chambers, J. K. and Trudgill, P.** (1998). *Dialectology*. Cambridge, UK: Cambridge University Press.
- Clarke, R. T., Rothery, P., and Raybould, A. F.** (2002). Confidence limits for regression relationships between distance matrices: estimating gene flow with distance. *Journal of Agricultural, Biological, and Environmental Statistics*, **7**(3): 361.
- Currie, T.E. and Mace, R.** (2012). The evolution of ethnolinguistic diversity. *Advances in Complex Systems*, **15**(01n02): 1150006.
- Derungs, C. and Samardžić, T.** (2018). Are prominent mountains frequently mentioned in text? Exploring the spatial expressiveness of text frequency. *International Journal of Geographical Information Science*, **3**(5): 856–873.
- Douglas, D. H.** (1994). Least-cost path in GIS using an accumulated cost surface and slopelines. *Cartographica: The International Journal for Geographic Information and Geovisualization*, **31**(3): 37–51.
- Dunn, M.** (2015). Language phylogenies. In O’Keeffe, A. and McCarthy, M. (eds), *The Routledge Handbook of Historical Linguistics*. London, New York: Routledge, pp. 190–211.
- Falck, O., Heblich, S., Lameli, A., and Südekum, J.** (2012). Dialects, cultural identity and economic exchange. *Journal of Urban Economics* **72**, 225–39.
- Frings, T.** (1948). *Grundlegung einer Geschichte der deutschen Sprache*. Halle (Saale): Max Niemeyer.
- Fröhlich, P., Frey, T., Reubi, S., and Schiedt, H.U.** (2004). Entwicklung des Transitverkehrs-Systems und deren Auswirkung auf die Raumnutzung in der Schweiz (COST 340). *Arbeitsberichte Verkehrs- und Raumplanung*, **208**. Zurich: IVT ETH Zurich. <http://www.ivt.ethz.ch/institut/vpl/publikationen/papers-2004.html>
- Glaser, E. and Bart, G.** (2015). Dialektsyntax des Schweizerdeutschen. In Kehrein, R., Lameli, A. and Rabanus, S. (eds), *Regionale Variation des Deutschen. Projekte und Perspektiven*. Berlin; Boston: de Gruyter, pp. 79–105.
- Goebl, H.** (1984). Dialektometrische Studien: Anhand italo-romanischer, rätoromanischer und galloromanischer Sprachmaterialien aus AIS und ALF, *Beihefte zur Zeitschrift für romanische Philologie*, Vol. 191-193 (3 volumes) Tübingen: Max Niemeyer, 289 p.
- Gooskens, C.** (2004). Norwegian dialect distances geographically explained. In Gunnarson, B.-L., Bergström, L., Eklund, G., Fridella, S., Hansen, L. H., Karstadt, A., Nordberg, B., Sundgren, E. and Thelander, M. (eds), *Language Variation in Europe. Papers from the Second International Conference on Language Variation in Europe ICLAVE*. Uppsala, Sweden: Uppsala University, pp. 195–206.
- Goossens, J.** (1969). *Strukturelle Sprachgeographie. Eine Einführung in Methodik und Ergebnisse*. Heidelberg: Winter.
- Grieve, J., Speelman, D., and Geeraerts, D.** (2011). A statistical method for the identification and aggregation

- of regional linguistic variation. *Language Variation and Change* 23(2): 193–221.
- Grober-Glück, G.** (1982). Die Leistungen der kulturmorphologischen Betrachtungsweise im Rahmen dialektgeographischer Interpretationsverfahren. In Halbband Erster (ed.), *Dialektologie. Ein Handbuch zur deutschen und allgemeinen Dialektforschung*. Berlin, New York: de Gruyter, pp. 92–113.
- Grollemund, R., Branford, S., Bostoen, K., Meade, A., Venditti, C., and Pagel, M.** (2015). Bantu expansion shows that habitat alters the route and pace of human dispersals. *Proceedings of the National Academy of Sciences*, 112(43): 13296–301.
- Haas, W.** (2010). A study on areal diffusion. In Auer, P. and Schmidt, J.E. (eds), *Language and Space. An International Handbook of Linguistic Variation*. Berlin, New York: de Gruyter Mouton, pp. 649–67.
- Heeringa, W. and Nerbonne, J.** (2001). Dialect areas and dialect continua. *Language Variation and Change*, 13(3): 375–400.
- Holenstein, A.** (2009). Reformation und Konfessionalisierung in der Geschichtsforschung der Deutschschweiz. *Archiv für Reformationsgeschichte*, 100(1): 65–87.
- Hotzenköcherle, R.** (1962). *Einführung in den Sprachatlas der deutschen Schweiz. A. Zur Methodologie der Kleinraumatlanten*. Bern: Francke.
- Hotzenköcherle, R. and Trüb, R.** (1962). *Sprachatlas der deutschen Schweiz*, vol.1. Bern: Francke.
- Hyvönen, S., Leino, A., and Salmenkivi, M.** (2007). Multivariate analysis of Finnish dialect data—an overview of lexical variation. *Literary and Linguistic Computing*, 22(3): 271–90.
- Jarvis, A., Reuter, H. I., Nelson, A., et al.** (2008). Hole-filled SRTM for the globe Version 4. Available from the CGIAR-CSI SRTM 90m Database (<http://srtm.csi.cgiar.org>, accessed 31 May 2019).
- Jeszczyszky, P., Stoeckle, P., Glaser, E., and Weibel, R.** (2017). Exploring global and local patterns in the correlation of geographic distances and morphosyntactic variation in Swiss German. *Journal of Linguistic Geography*, 5(2): 1–23.
- Jongen, R.** (1982). Theoriebildung der strukturellen Dialektologie. In Ungeheuer, G. and Wiegand, H.E. (eds), *Dialektologie. Ein Handbuch zur deutschen und allgemeinen Dialektforschung*. Berlin; New York: de Gruyter, pp. 248–77.
- Knobloch, C.** (2010). Language and space: The kulturmorphologische Ansatz in dialectology and the German language space ideology, 1920–1960. In Auer, P. and Schmidt, J.E. (eds), *Language and Space. An International Handbook of Linguistic Variation*. Berlin, New York: de Gruyter Mouton, pp. 107–25.
- Kremer, L.** (1984). Die niederländisch-deutsche Staatsgrenze als subjektive Dialektgrenze. *Driemaandelijke Bladen*, 36, 76–83.
- Lameli, A.** (2013). *Strukturen im Sprachraum. Analysen zur arealtypologischen Komplexität der Dialekte in Deutschland*. Berlin; Boston: de Gruyter.
- Lameli, A., Nitsch, V., Südekum, J., and Wolf, N.** (2015). Same same but different: dialects and trade. *German Economic Review*, 16(3): 290–306.
- Leemann, A., Kolly, M.-J., Purves, R., Britain, D., and Glaser, E.** (2016). Crowdsourcing language change with smartphone applications. *PloS One*, 11(1): e0143060.
- Legendre, P.** (1993). Spatial autocorrelation: trouble or new paradigm? *Ecology*, 74(6): 1659–73.
- Löffler, H.** (2003). *Dialektologie: eine Einführung*. Tübingen: Gunter Narr.
- Mace, R. and Holden, C. J.** (2005). A phylogenetic approach to cultural evolution. *Trends in Ecology & Evolution*, 20(3): 116–21.
- Mace, R. and Pagel, M.** (1995). A latitudinal gradient in the density of human languages in North America. *Proceedings of the Royal Society of London B: Biological Sciences*, 261(1360): 117–21.
- Nerbonne, J.** (2010). Measuring the diffusion of linguistic change. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 365(1559): 3821–8.
- Nerbonne, J. and Heeringa, W.** (2007). Geographic distributions of linguistic variation reflect dynamics of differentiation. *Roots: Linguistics in Search of its Evidential Base*, 96, 267–97.
- Nerbonne, J.** (2009). Data-driven dialectology. *Language and Linguistics Compass*, 3(1). 175–98.
- Nichols, J.** (2013). The vertical archipelago: Adding the third dimension to linguistic geography. In Auer, P., Hilpert, M., Stukenbrock, A., and Szmrecsanyi, B. (eds), *Space in Language and Linguistics: Geographical, Interactional, and Cognitive Perspectives*. Berlin: Walter de Gruyter, 38–60.
- Niebaum, H. and Macha, J.** (2006). *Einführung in die Dialektologie des Deutschen*. 2. Aufl. Tübingen: Niemeyer.

- Pröll, S., Pickl, S., and Spettil, A. (2014). Latente Strukturen in geolinguistischen Korpora. In Elmentaler, M., Hundt, M., and Schmidt, J.E. (eds), *Deutsche Dialekte Konzepte, Probleme, Handlungsfelder*. Stuttgart: Steiner.
- Rosenblatt, M. (1956). A central limit theorem and a strong mixing condition. *Proceedings of the National Academy of Sciences*, 42(1): 43–7.
- Sankoff, G. (2002). Linguistic outcomes of language contact. In Chambers, J.K., Trudgill, P. and Schilling-Estes, N. (eds), *The Handbook of Language Variation and Change*. Malden, MA, Oxford: Blackwell Publishing Ltd., pp. 638–68.
- Scherrer, Y. and Stoeckle, P. (2016). A quantitative approach to Swiss German–Dialectometric analyses and comparisons of linguistic levels. *Dialectologia et Geolinguistica*, 24(1): 92–125.
- Séguy, J. (1971). La relation entre la distance spatiale et la distance lexicale. *Revue de linguistique romane*, 35, 335–57.
- Sherrin, N. (2008). *Oxford Dictionary of Humorous Quotations*. Oxford, UK: Oxford University Press.
- Siart, C., Eitel, B., and Panagiotopoulos, D. (2008). Investigation of past archaeological landscapes using remote sensing and GIS: a multi-method case study from Mount Ida, Crete. *Journal of Archaeological Science*, 35(11): 2918–26.
- Skiena, S. (1990). *Dijkstra's Algorithm. Implementing Discrete Mathematics: Combinatorics and Graph Theory with Mathematica*. Reading, MA: Addison-Wesley, pp. 225–27.
- Sonderegger, S. (2003). Aspekte einer Sprachgeschichte der deutschen Schweiz. *Sprachgeschichte*. In *Teiband, Ein Handbuch zur Geschichte der deutschen Sprache und ihrer Erforschung*, 2nd edn. Berlin; New York: de Gruyter, 2825–88.
- Spruit, M. R. (2006). Measuring syntactic variation in Dutch dialects. *Literary and Linguistic Computing*, 21(4–Progress in Dialectometry: Toward Explanation), 493–506.
- Spruit, M. R., Heeringa, W. and Nerbonne, J. (2009). Associations among linguistic levels. *Lingua*, 119, 1624–42.
- Stein, M. L. (2012). *Interpolation of Spatial Data: Some Theory for Kriging*. New York: Springer Science & Business Media.
- Szmrecsanyi, B. (2012). Geography is overrated. In Hansen, S., Schwarz, C., Stoeckle, P., and Streck, T., (eds), *Dialectological and Folk Dialectological Concepts of Space: Current Methods and Perspectives in Sociolinguistic Research on Dialect Change*. Berlin, Boston: Walter de Gruyter, pp. 215–31.
- Tobler, W. (1993). *Three Presentations on Geographical Analysis and Modeling*. NCGIA.
- Trudgill, P. (1974). Linguistic change and diffusion: description and explanation in sociolinguistic dialect geography. *Language in Society*, 3(2): 215–46.
- van Etten, J. (2017). R package gdistance: distances and routes on geographical grids. *Journal of Statistical Software*, 76(13), 1–21.
- Valls, E., Wieling, M., and Nerbonne, J. (2013). Linguistic advergence and divergence in north-western Catalan: adialectometric investigation of dialect leveling and border effects. *Literary and Linguistic Computing*, 28(1): 119–46.
- Vatter, A. (2002). *Kantonale Demokratien im Vergleich: Entstehungsgründe, Interaktionen und Wirkungen politischer Institutionen in den Schweizer Kantonen*. Opladen: Leske + Budrich.
- de Vriend, F., Giesbers, C., van Hout, R., and ten Bosch, L. (2008). The Dutch-German border: relating linguistic, geographic and social distances. *International Journal of Humanities and Arts Computing*, 2(1–2): 119–34.
- Wieling, M., Nerbonne, J., and Baayen, R. H. (2011). Quantitative social dialectology: explaining linguistic variation geographically and socially. *PloS One*, 6(9): e23613.
- Wieling, M., Shackleton R. G., Jr, and Nerbonne, J. (2013). Analyzing phonetic variation in the traditional English dialects: simultaneously clustering dialects and phonetic features. *Literary and Linguistic Computing*, 28(1): 31–41.
- Woolhiser, C. (2005). Political borders and dialect divergence/convergence in Europe. In Peter, A., Hinskens, F. and Kerswill, P. (eds), *Dialect Change. Convergence and Divergence in European Languages*. Cambridge: Cambridge University Press, pp. 236–62.
- Woolhiser, C. (2011). Border effects in European dialect continua: dialect divergence and convergence. In Kortmann, Bernd, and van der Auwera Johan (eds), *The Languages and Linguistics of Europe: A Comprehensive Guide*. Berlin; Boston: de Gruyter, pp. 501–24.

Notes

- 1 Alain Berset, in 'Das Magazin', p.20, vol. 36, September 2017.

- 2 'Syntaktischer Atlas der deutschen Schweiz' (Syntactic Atlas of German-speaking Switzerland) <http://www.dialektsyntax.uzh.ch/de.html>
- 3 A comprehensive list can be found in Jeszensky *et al.* (2017).
- 4 <https://www.swisstopo.admin.ch/en/home/products/height/dhm25.html>
- 5 <https://www.bfs.admin.ch/bfs/de/home/dienstleistungen/geostat/geodaten-bundesstatistik/administrative-grenzen.html>
- 6 <https://www.bfs.admin.ch/bfs/de/home/statistiken/raum-umwelt/nomenklaturen/msreg.html>
- 7 In contrast to standard spatial regression, where individual observations can be spatially represented as points or polygons on a map, in our case, observations can be represented as spatial 'lines', connecting two SADS municipalities. Given the large number of lines, we aggregate individual model residuals to smoothed line-density maps.