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Identifying drivers of forest clearances in Switzerland

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A R T I C L E I N F O

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A B S T R A C T

Deforestation is prohibited in Switzerland, as in most European countries. Nevertheless, exemptions from the ban on forest clearing may be granted, mostly for infrastructure purposes. However, surprisingly little is known about the drivers of deforestation outside of the tropics and developing countries. In this paper, we present results from a spatial econometric analysis of the drivers of forest clearances in Switzerland between 2001 and 2017. The analysis is based on a complete data set on forest clearances, which are defined as land-use and not just land-cover changes. We observe that landscape metrics are pertinent predictors of forest clearances in Switzerland. Unlike common findings on drivers of deforestation in the tropics, in Switzerland, (1) variables related to agriculture exhibited no explanatory power, (2) we found a positive effect of altitude on forest clearances in the Alps, and (3) a negative effect of the population density. We close by critically reviewing our results with regard to the use of spatial and non-spatial regression methods used in the analysis.

1. Introduction

Urbanization is a global megatrend (Ritchie and Roser, 2018; UN-Habitat, 2020; van Vliet et al., 2017). Overall, Europe has the highest share of urban area (van Vliet et al., 2017). The constantly increasing urban land take, sprawl and need for infrastructure leads to land-use conflicts, pressure on protected areas (EEA and FOEN, 2016; Hennig et al., 2015; Triantakonstantis and Stathakis, 2015; van Vliet et al., 2017), and to an increased competition for land (Haberl, 2015; Smith et al., 2010). Among the increasing pressures on forests, urban expansion and infrastructure development are the main reasons for deforestation in Europe (EEA, 2016). However, European forest areas are still net growing (EEA, 2016).

Drivers of deforestation and their evolution over time have been extensively studied (Austin et al., 2017; Leblois et al., 2017; Rudel et al., 2009). This is especially true for tropical countries, where the forest area is continuously decreasing (Keenan et al., 2015). In general, agriculture in its various forms is regarded as the most important driver of deforestation (DeFries et al., 2010; Geist and Lambin, 2002; Hosonuma et al., 2012; Kissinger et al., 2012; Pendrill et al., 2022). Regionally, however, the drivers of deforestation related to agriculture are known to vary (Curtis et al., 2018; Hosonuma et al., 2012). In Latin America and in Asia, commercial agriculture is the dominant driver of deforestation (Curtis et al., 2018; Hosonuma et al., 2012; Rudel et al., 2009), whereas in Africa, it is subsistence or small-scale agriculture (Curtis et al., 2018; Hosonuma et al., 2012; Tyukavina et al., 2018). Further, there is a trend to bigger clearings (Austin et al., 2017) and some evidence that deforestation nowadays is less state- and more market-driven than it was in the past (Rudel, 2007). However, surprisingly little is known about the drivers of deforestation outside of the tropics and developing countries (Busch and Ferretti-Gallon, 2017; Wang and Qiu, 2017; Zambrano-Monserrate et al., 2018).

Current quantitative forest research mostly builds on the analysis of land-cover change using remote sensing and machine learning (Austin et al., 2017; Curtis et al., 2018; Leblois et al., 2017). In Europe, especially in Switzerland as a case in point, quantitative forest research, at least until now, has focused more on forest transition, land abandonment and reforestation (Hirschi et al., 2012; Loran et al., 2016, 2017; Mather and Fairbairn, 2000). Across Europe, remote sensing-based analysis of forest disturbances has made substantial progress. However, inferring land-use from land-cover to distinguish forest clearances from e.g. ordinary clear-cuts, wind-throws, wildfires etc., is still difficult, especially for smaller plots (Pendrill et al., 2022; Senf and Seidl, 2020). The environmental and socio-economic setting is substantially different in European countries, which calls for a different narrative to explain forest clearances.

Within the broad field of land system science, there is an inconsistent usage of related conceptual terms like drivers, driving forces, causes,

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factors or (spatial) determinants (Bürgi et al., 2004; Lambin et al., 2003; Meyfroidt, 2016). *Drivers* and *driving forces* are often considered synonyms, whereas the term *causes* emphasizes a causal mechanism (Meyfroidt, 2016), and land-use or land-cover change is considered as the result of a combination of different drivers or causes (Hersperger et al., 2010). These are often separated in underlying or indirect drivers that affect the proximate or direct drivers causing land-use/cover change, e.g. deforestation (Kissinger et al., 2012). Within the newer remote sensing literature, especially on deforestation, the terms driver or direct driver are often used more in the sense of biophysical processes or human activities that affect or change land-cover, hence cannot necessarily be considered as land-use changing (Curtis et al., 2018; Tyukavina et al., 2018). The many frameworks explaining land-use and land-cover change can be roughly divided into two approaches based on the availability of information about agents (Hersperger et al., 2010): the widely-used framework by Kaimowitz and Angelsen (1998) uses information about agents, whereas the prominent proximate causes and underlying driving forces framework by Geist and Lambin (2002) does not (Meyfroidt et al., 2018; van Khuc et al., 2018). The latter, simpler framework linking drivers directly to land-change is more useful for exploratory correlation analyses than to identify causal relationships (Hersperger et al., 2010).

For disentangling the effects of the drivers of deforestation, spatially explicit econometric analyses are argued to be particularly suitable (Busch and Ferretti-Gallon, 2017). Although spatial econometric methods can account for spatial autocorrelation and provide more accurate estimates (Elhorst, 2014; Ward and Gleditsch, 2019; Wheeler et al., 2013), they are rarely used in the literature on drivers of deforestation (Busch and Ferretti-Gallon, 2017; Ferrer Velasco et al., 2020). The number of methods available to account for spatial dependence or autocorrelation in the residuals (error terms), specifically of logit models, is limited. Often, the computational demands grow exponentially with increasing numbers of observations. Therefore, spatial segregation and the choice of spatial resolution must be made with appropriate care. While autologistic regression and geographically weighted logistic regression are imprecise and of limited use (Dormann, 2007; Dormann et al., 2007), GMM (Generalized Method of Moments) is not suited for large data sets (Smirnov, 2010). Wavelet Revised Models (WRM) (Carl and Kühn, 2010) and especially linearized GMM spatial logit models (Klier and McMillen, 2008) have been shown to be suitable for huge numbers of observations.

In this paper, we investigate drivers of forest clearances in Switzerland, a country situated in a temperate climatic zone in the middle of Europe, where agriculture is largely prevented as a reason for forest clearances. In particular, we analyze whether there are similarities or differences in drivers across spatial entities (i.e. forest regions) using non-spatial logit and robust logit models, and with linearized GMM spatial logit models (Klier and McMillen, 2008). We build on a unique national forest clearances database, that contains information on all clearance permissions between 2001 and 2017 for Switzerland. Troxler and Zabel (2021) find that from 2001 to 2017, on average 185 ha of forest were cleared annually, mainly for infrastructure purposes, but the reasons for forest clearances are highly heterogeneous across the country. Forest clearances are defined as land-use and not just land-cover changes. Our study marks a step toward the development of a new narrative to explain (infrastructure-related) deforestation that can apply to other European countries. Further, our analysis is land-use oriented and does not rely on land-cover information as a proxy. Moreover, the paper contributes to the existing body of literature on urban and related landscape change by closely investigating relationships between landscape metrics with forest clearances. Finally, the paper makes a methodological contribution by comparing the differences between traditional regression methods and one that can account for spatial autocorrelation.

2. Materials & methods

2.1. Case study description

Switzerland's population has increased during the past decades from 4.7 million in 1950 to 8.6 million in 2019 (FSO, 2020). The trends in population growth are spatially heterogeneous and particularly significant in the Plateau area (FSO, 2015). As in many other European countries, Switzerland has witnessed strong urbanization trends; 85% of its population now lives in urban areas (FSO, 2020). While forest and agricultural area each make up for about 1/3 of the area, and unproductive area makes up for 1/4, the settlement area covers only 7.5% of the total area (FSO, 2015). In a comparatively small country like Switzerland, the changes in population densities have however substantially increased competition for land, including forest. Mann (2009) argues that apart from urban sprawl, the Swiss landscape is exposed to what he termed *rural sprawl*, i.e. 'building activities in rural landscapes that [change or even] degrade the scenic and/or environmental quality of the area'. Mann (2009) states that forests are largely exempted from rural sprawl due to Switzerland's stringent forest protection. However, just because forest clearances should not exist does not mean that they do not exist.

In Switzerland, the forest area is generally increasing, especially in the Alps. In the Plateau, where the greatest pressure is exerted on the forest (Troxler and Zabel, 2021), the area has remained constant or even slightly decreased (FSO, 2018b). The Swiss Federal Forest Act (ForA; SR 921.0) prohibits deforestation since 1902 (Mather and Fairbairn, 2000). Thus, the Swiss forest is conserved in its area and spatial distribution. However, exemptions from the ban on forest clearing may be granted under well-defined conditions, i.e. when important interests outweigh the ones of forest conservation (ForA; SR 921.0). Most of the projects that received a clearance permission are infrastructure projects. The final decisions on clearance permissions are taken at the federal level, which means that analysis of clearances should be conducted at the national rather than sub-jurisdictional level. Usually, cleared forest land must be compensated through afforestation in the same region (ForA).

The Federal Office for the Environment (FOEN) maintains a database for all authorized forest clearance permissions. Since it also contains their coordinates, spatially explicit analyses of clearances become feasible. For this study, we were provided with data from 2001 to 2017. In the forest act of Switzerland, forest clearances are defined as either temporary or permanent changes in use of forest land for non-forestry purposes. This definition emphasizes the repurposing of land in strong contrast to land-cover changes like clear-cuts or any other form of forestry practices that accordingly are not considered deforestation. Since this gives us a less common definition for deforestation, we use the term forest clearances instead to emphasize that they are legally authorized and based on a change in land-use rather than land-cover. Temporary clearances are often more important in terms of area than definitive clearances (Troxler and Zabel, 2021). Most clearance projects demand both types of area because construction work often needs more space than the facilities itself. It is a unique situation to have a complete data set consisting of all authorized forest clearances on a country level. This opens up the opportunity to address much more targeted or specific research questions than using land-cover information only.

2.2. Groups of drivers

The variable selection was only partially guided by the literature on drivers of deforestation, which mainly covers tropical regions. However, there is closely related research that helped in variable assessment, i.e. on forest regrowth, land abandonment, land take, and urban sprawl (Colsaet et al., 2018; Loran et al., 2017; van Vliet et al., 2015; Weilenmann et al., 2017). Furthermore, the EEA (2016) identified urban expansion and infrastructure development as the main reasons for deforestation in Europe, and the Swiss forest legislation largely prevents agriculture as a reason for forest clearances. Troxler and Zabel (2021) grouped Switzerland's forest clearances in nine distinct categories of clearance reasons ('transportation', 'water construction', 'water supply', 'quarry sites', 'waste disposal and recycling', 'energy and lines', 'constructions', 'sport and tourism', and 'miscellaneous'.). These gave hints about the type, frequency, spatial distribution and extent of reasons.

Combining different strands of literature, we propose three groups of drivers to explain the location of forest clearances in Switzerland: (i) predisposing environmental factors, (ii) socio-economic factors, and (iii) land-use related factors (i.e. landscape metrics). Predisposing environmental factors are land characteristics (Geist and Lambin, 2002) that are considered to be relatively unimportant in causing a phenomenon, but can be important to determine exact locations (Meyfroidt, 2016). Variables in this category, that have previously been found to be correlated with forest clearances, include altitude, roughness, slope, and proximity to water (Busch and Ferretti-Gallon, 2017; Colsaet et al., 2018; Geist and Lambin, 2002; Wheeler et al., 2013). The socio-economic factors category harbors mostly variables related to population and settlement structure. Important socio-economic variables often used to explain deforestation are population size as well as population increase and accessibility (Busch and Ferretti-Gallon, 2017; Colsaet et al., 2018; DeFries et al., 2010; Kissinger et al., 2012; Leblois et al., 2017). While the previous two groups of explanatory factors are well-established in the deforestation literature, we add land-use related factors (i.e. landscape metrics) as a third group. Landscape metrics are 'simple measures of landscape structure' (Kupfer, 2012) that condense complex spatial patterns to simple numbers, which are then easily comparable in contrast to the patterns. While they are very common in landscape ecology (Hesselbarth et al., 2019; Kupfer, 2012; Lausch et al., 2015), there are hardly any studies that use them to analyze drivers of deforestation.

2.3. Data and its processing

In a first step, we allocated the coordinates of the authorized forest clearances from 2001 to 2017 to the 100 m resolution raster grid of Switzerland's land-use statistic 2004/09 (FSO, 2015). The binary (dummy) response variable *clear* takes the values 1 or 0 to indicate whether or not coordinates of past forest clearances lie within the cells of the raster grid. Of the 9494 clearance sites, 4.6% of the coordinates were missing or >100 m away from the border of the municipality in which they were supposed to be located, and were therefore excluded from the analysis. The land-use statistic was used to determine between five types of land-use: (1) settlement area, (2) agricultural area, (3) forest area, (4) unproductive area, as well as (5) waters (lakes and streams). The land-use, however, was estimated only at the center of each raster cell. Of the grid cells with forest clearances, 45.6% were on forest area, 25.2% on settlement area, and 20.6% on agricultural area.

The hectare-sized raster grid was aggregated to a raster with 500 m resolution (¼ km^2) to obtain a larger cell size and thus also a reduced cell number due to three reasons. Firstly, even with a subdivision into smaller spatial entities (forest regions), the spatial regression methods showed exponential RAM demands with increasing units of observation (raster cells). Hence, this is the smallest grid size for which we could apply the spatial methods for all forest regions. Secondly, spot checks revealed that the clearance coordinates are not always completely accurate and therefore the use of a larger raster grid absorbs some of this uncertainty. Thirdly, having more than one land-use information per raster cell opens up the opportunity to estimate many different landscape metrics (Kupfer, 2012). In fact, there are now 25 land-use information cells within one cell of the raster used for the analysis (500 m * 500 m). Of the >100 different landscape metrics (Hesselbarth et al., 2019), many are strongly correlated with each other (Bosch et al., 2020). We thus first selected the simplest one, the total class area (ca) for the 5 different land-use categories. It measures the total area of a land-use class, e.g. pixels of forest or agriculture within a defined spatial area. Especially ca1 (settlement) and ca3 (forest) had a strong correlational influence on the response variable clear. Since the fundamental information about a landscape's configuration is provided by compositional (number and abundance) and configurational (spatial arrangement) information together (Nowosad and Stepinski, 2019), combining both traits, we applied some novel and thus not yet well-established information theory-based complexity metrics, e.g. Shannon entropy, and Joint entropy (Nowosad and Stepinski, 2019), provided in the landscapemetrics package (Hesselbarth et al., 2019). Raster cells partially extending beyond the national borders were omitted from the analysis when the percentage of land-use rasters inside was <90%.

Based on a shapefile from the Swiss Federal Statistical Office (FSO), derived from biogeographical regions (Gonseth et al., 2001) adjusted by municipality borders (2016), the data set was assigned to the 5 forest regions of Switzerland (Jura, Plateau, Prealps, Alps and Southern Alps). Due to the major differences across these regions, it makes sense to separately investigate how the explanatory variables affect the response variable clear.

To compare the grid cells with and without authorized forest clearances between 2001 and 2017 across the five forest regions (response variable clear), Table 1 provides information on the exact numbers (of observations), while the map in Fig. 1 gives an overview of the spatial distribution. The map also visualizes the forest regions as spatial entities and units of analysis. Raster cells exhibiting >80% settlement area are marked in grey to emphasize urban areas (i.e. cities).

In a second step, we compiled a set of variables used in the regression analyses (see section 2.4). A digital elevation model (DHM) with 25 m resolution (SWISSTOPO DHM25) was used to derive a set of explanatory variables based on altitude. The slope, aspect, TPI (Topographic Position Index), TRI (Terrain Ruggedness Index) and roughness were calculated using the eight surrounding neighbor cells.

After rasterizing the polygon data of lakes and streams in 2013 (without streams with an outflow [m^3/s] categorized as small or middle), it was possible to calculate the distance to waters for every raster cell. Another distance-related variable was built based on polygon data representing travel time and accessibility in 2017 (NPVM: 'Accessibility by road depending on travel time and potential at destination') (ARE, 2020).

The Swiss Federal Statistical Office's (FSO) 'Population and Households Statistics' (STATPOP) provide spatially explicit population data in a 100 m raster. The total permanent resident population of the years 2010 and 2017 were used (FSO, 2013, 2018a). Unfortunately, there are no comparable data sets for earlier years. Also, due to data protection reasons, raster cells with <4 inhabitants are missing in the data set.

One disadvantage of socioeconomic variables is that many are not (or cannot be) spatially explicit. Hence, some variables were only known at the community level (Loran et al., 2017). One approach to deal with this would be to aggregate all the data to the community level (Wang and Qiu, 2017). Since we were interested in a much more fine-grained analysis, we instead merged the community level socioeconomic variables to the raster cells via the Community Identification Number (swissBOUNDARIES3D 2018). However, probably because of the limited variability, since all raster cells in a community have the same values, these variables had to be dropped in favor of others with more

Table 1
Numbers of raster cells (500 m * 500 m) per forest region (response variable clear).

Forest region	# cells without forest clearances (0)	# cells with forest clearances (1)	%
Jura	18'280	486	2.6
Plateau	37'438	1'439	3.7
Prealps	25'670	892	3.4
Alps	63'624	1'982	3
Southern Alps	13'521	416	3

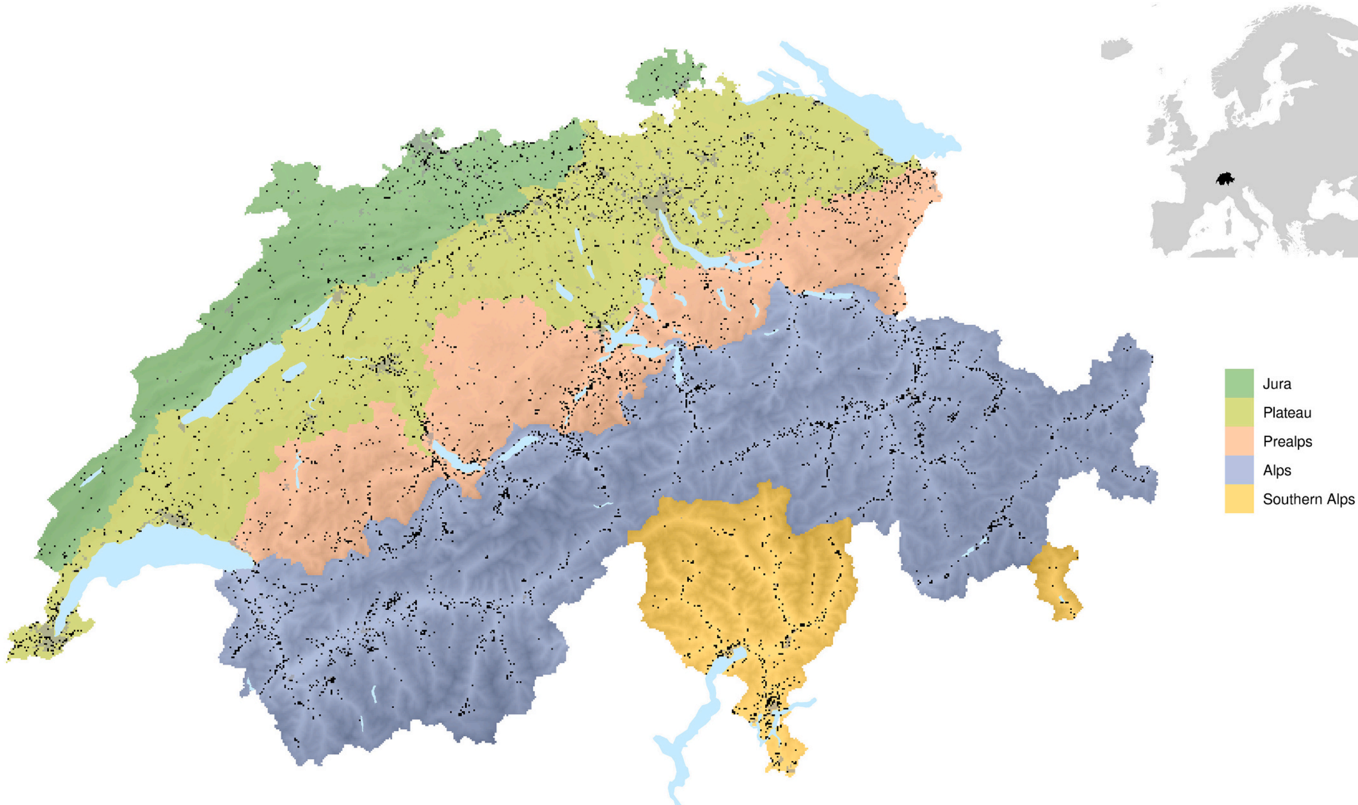

Fig. 1. Spatial distribution of the raster cells with authorized forest clearances between 2001 and 2017 (binary response variable clear), represented in black.

explanatory power.

A comprehensive list of the used variables is to be found in Table 2. In the model selection process, in order to avoid collinearity, the variable composition was chosen on the basis of correlation and systematically controlled using the variance inflation factor (VIF). Further, we applied a stepwise algorithm based on the Akaike information criterion (AIC) to choose a meaningful model that fits all forest regions.

2.4. Regression methods

Due to the nature of the dichotomous (binary) response variable clear (0/1), which provides information whether or not coordinates of past forest clearances lie within the cells of the raster grid, it is possible to use presence/absence (logit) models. These regression models were estimated using two non-spatial methods, (1) logit and (2) robust logit, and a spatial method, (3) linearized GMM spatial logit. The latter is a binary spatial autoregressive model, that accounts for spatial autocorrelation in the response variable clear, e.g. when there are clearance clusters. The term ‘robust’ (method 2) refers to estimations and standard errors that are robust to violations of model assumptions, i.e. is less sensitive to outliers compared to OLS (Wilcox, 2022).

The linearized GMM spatial logit is an approximation of the GMM (Generalized Method of Moments) spatial lag model that is computationally much more efficient as it does not rely on repeated inversion of large matrices. The estimation procedure starts with a non-spatial logit followed by a two-stage least squares estimation of the linearized model using spatially weighted averages of nearby values as instruments (Klier and McMillen, 2008). It is a spatial lag model, hence a model with a spatially lagged (weighted) dependent variable. It assumes the form $Y = \rho WY + \beta X + \varepsilon$. Here, Y is the binary dependent variable (clear), W is the contiguity, weight, or neighborhood matrix, X represents the explanatory variable(s), ε is the error term, and β and ρ are the parameters to be estimated. The only difference to a traditional non-spatial logit model is the spatial autoregressive term with its parameter ρ. It measures the strength and direction of spatial dependence, while the prespecified neighborhood matrix W determines how the dependent variable Y can be affected by neighboring observations. A positive value for the spatial autoregressive parameter (ρ) implies spatially clustered forest clearances, whereas a negative value implies spatially dispersed forest clearances (Klier and McMillen, 2008).

As the linearized GMM spatial logit models rely on an arbitrary neighborhood matrix (W), we used two different neighborhood distances to construct the matrices, namely a radius of 2 km and a radius of 10 km. Using a sensitivity analysis of the effects of different neighborhood distances on estimates and their standard errors, we found that these two radii form roughly the bandwidth of possible results. Hence, the true estimates must be somewhere in between the estimates of these two neighborhood distances.

Eq. 1 shows how the inverse distance weighting (IDW) of the neighborhood matrices was conducted, and run using the weighting factors $\alpha = 1$ and the more common $\alpha = 2$. The weight coming from neighboring observations used to adjust for spatial autocorrelation diminishes with distance. With $\alpha = 2$ the weight diminishes more strongly than with $\alpha = 1$. Far away observations thus receive less weight.

$$W_{(IDW)} = \frac{D_{ij}^{-\alpha}}{\sum_{i=1}^{n} D_{ij}^{-\alpha}} \tag{1}$$

The data work was carried out with R, version 3.6.3, using the following packages: McSpatial 2.0, robustbase 0.93-6, spdep 1.1-5, raster 3.3-13, landscapemetrics 1.5.0. In an earlier version of this article, as an alternative to GMM models, we also applied Wavelet Revised Models (WRM) (Carl and Kühn, 2010), whose coefficients, however, correspond to those of the logit models, only the standard errors are different because they account for spatial autocorrelation.

Table 2
A comprehensive list of the used variables.

Variable		Data Source
Predisposing environmental factors:		
Altitude	[m]	
derived based on 8 surrounding cells:		
Slope	[°]	
Terrain Ruggedness Index (TRI)	[m]	
Topographic Position Index (TPI)	[m]	
Roughness	[m]	
Aspect	[°]	
Flow direction (of water)		Swisstopo DHM25
Rivers (2013)	0/1, area	
Lakes (2008)	0/1, area	
Waters (Lakes + Rivers)	0/1, area	
Distance to waters	[m]	River typology (FOEN), FSO
Socio-economic factors:		
Total population in 2017 and 2010		
Population change (2017–2010)		FSO
Building zones (2017)	0/1, area	
Distance to building zones	[m]	
Accessibility by road (NPVM) (2017)		ARE, National passenger transport model (ARE)
On community level:		
Total area	[km^2]	
Settlement area	[%]	
Change in settlement area (79/85-04/09)	[ha]	
Agricultural area	[%]	
Change in agricultural area (79/85-04/09)	[ha]	
Forest and woodland	[%]	
Unproductive area	[%]	
Population (2017)		
Population change (2010-2017)	[%]	
Population density	[km^{-2}]	
Foreigners	[%]	
Age distribution (0-19, 20-64, 65+)	[%]	
Birth and death rate		
Number of private households		
Average household size		
Total employees		
Employees in the 1st sector		
Employees in the 2nd sector		
Employees in the 3rd sector		
Total workplaces		
Workplaces in the 1st sector		
Workplaces in the 2nd sector		
Workplaces in the 3rd sector		
Vacant apartment rate		
Newly built dwellings (per 1000 inhabitants)		
Social quota		FSO (Regional portraits 2019: communes)
Land-use related factors:		
Total (class) areas:		
Settlement area (`ca1`)		
Agricultural area (`ca2`)		
Forest area (`ca3`)		
Unproductive area (`ca4`)		
Waters (lakes and streams) (`ca5`)		
Complexity metrics:		
Conditional entropy		
Shannon entropy		
Joint entropy		
Mutual information		Swiss land-use statistics (2004/09)

2.5. Presentation of regression results

In order to enhance comparability between model results, we used 'small multiple' plots (Kastellec and Leoni, 2007) to present the regression coefficients and their corresponding Wald confidence intervals (Estimate ±1.96 * Standard Error). Estimates, whose confidence intervals do not include 0, can be considered statistically significant. The direction of the effect can be read from the sign of the estimate. However, the confidence interval of the estimate alone does not allow any statement about the size of the effect.

To get a fully comparable measure also of the magnitude and thus the (relative) importance of effects of different explanatory variables, not only of the statistical significance, also standardized coefficients were computed. Hence, the estimates and their confidence intervals were multiplied with the standard deviation of the respective variables. This procedure allows for a direct comparison of which effects are more relevant than others (Menard, 2011; Stahel, 2021). For the sake of an enhanced comparability, all effects were plotted on the same scale (x-axis) and were pseudo-log transformed.

3. Results

Fig. 2 shows the regression coefficients and their corresponding confidence intervals. The linearized GMM spatial logit models were estimated using radii of 2 km (brown tones) and 10 km (green tones) and weighting values (α) of 1 (lighter colors) and 2 (darker colors). The variables exhibiting the greatest explanatory power are: altitude, slope, topographic position index (TPI), distance to waters (dist2waters), settlement area (ca1), forest area (ca3), unproductive area (ca4), joint entropy (joinent), total population in 2017 (B17TOT), population change between 2010 and 2017 (dpop1710), and accessibility by road (NPVM).

The variable altitude shows an almost consistent pattern across the forest regions. While the logit and robust logit estimates find statistically significant negative effects, the estimates of the linearized GMM spatial logit models are non-significant, except in the Alps, where we see a statistically significant positive effect. Comparing just the estimates of the linearized GMM spatial logit, the models with $\alpha = 1$ and $r = 10$ km considerably deviate to the left. Hence, the weighting factor shows an unexpectedly large influence on the estimates.

For slope, we find negative effects on the probability for forest clearances in the Alps and in the Southern Alps, whereas in the rest of Switzerland, the effect seems to be between not significant to positive. Because we estimated an interaction between slope and the joint entropy (joinent), slope measures only the effect when joinent is zero, i.e. in uniform landscapes.

Topographic Position Index (TPI) has no effect on the probability for forest clearances in the Jura, the Plateau, and in the Southern Alps. For the Prealps and the Alps, however, we find statistically significant negative effects. Since it measures the difference between the value of a raster cell and the mean value of its neighbors, depressions, craters or valleys (negative TPI) seem to have a higher probability for forest clearances there.

Distance to waters (dist2waters) has no effect on clearances in the Jura and the Plateau. In the rest of Switzerland, however, there seems to be a statistically significant negative effect. Hence, raster cells that are closer to waters have a higher probability for forest clearances.

The total population in 2017 (B17TOT) has an overall negative effect on the probability for forest clearances. This means that clearances tend to be located in less populated areas. However, the effect is only consistently statistically significant in the Jura. In the Alps and in the Southern Alps, only the linearized GMM spatial logit models are statistically significant, whereas the logit and robust logit models are not.

The population change between 2010 and 2017 (dpop1710) has clearly no effect in the Prealps, the Alps and in the Southern Alps. In the Jura, however, it has a statistically significant positive effect. Hence,

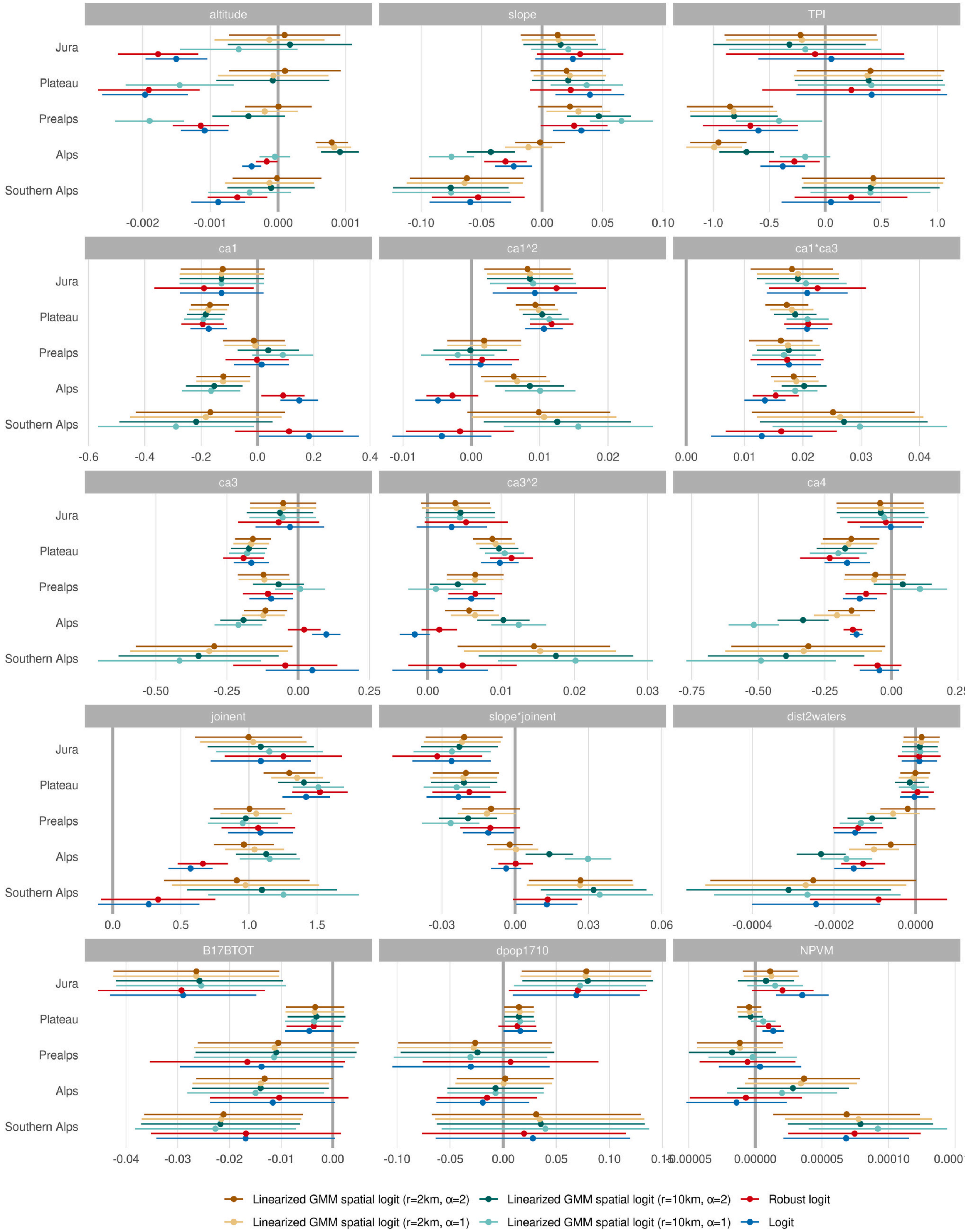

Fig. 2. Regression coefficients and corresponding confidence intervals. Every explanatory variable has its own scale on the x-axis and is horizontally stratified in forest regions (y-axis) and color-coded for the different regression methods. The linearized GMM spatial logit models were estimated using radii of 2 km (brown tones) and 10 km (green tones) and weighting values (α) of 1 (lighter colors) and 2 (darker colors).

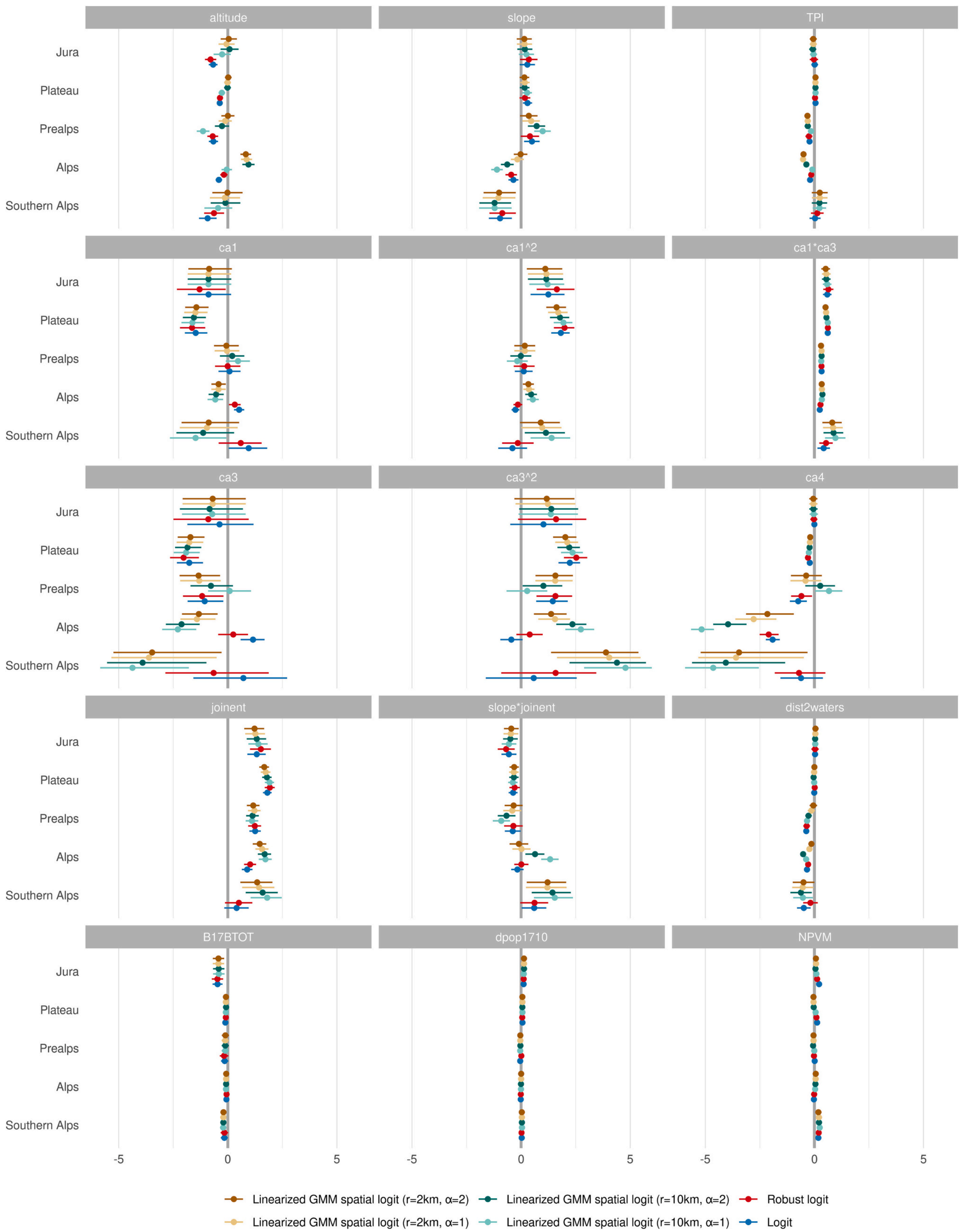

Fig. 3. Standardized coefficients as a mean of the effect sizes and thus of the relative importance of the variables. For an enhanced comparability, the estimates are pseudo log transformed and on the same scale (x-axis).

raster cells exhibiting a growing population have a higher probability for forest clearances there. The same applies for the Swiss Plateau, although there the effect is not entirely clear (borderline significance).

The accessibility by road (NPVM) is positively statistically significant only in the Southern Alps. There, a higher accessibility comes with a higher probability for forest clearances. In the Jura and in the Plateau region, only the logit models show a statistically significant positive effect.

For the settlement area (ca1) and the forest area (ca3) per raster cell, also quadratic effects were estimated. Thus, the effects of these variables cannot be interpreted without also considering the effects of $ca1^2$ and $ca3^2$. Without quadratic terms, ca1 and ca3 would have a positive linear effect on clear, but including the quadratic terms in the models reveal in most cases a U-shaped effect on the response variable. For these two terms, however, also interaction effects were estimated (ca1*ca3) which changes the interpretation of the involved terms. Because of the interaction, the settlement area estimates ($ca1 + ca1^2$) measure the effect on the probability for forest clearances only when there is no forest area in the respective raster cells ($ca3 = 0$), whereas the forest area estimates ($ca3 + ca3^2$) measure the effect when there is no settlement area ($ca1 = 0$). The interaction between settlement area (ca1) and forest area (ca3) is positive and highly statistically significant across all forest regions and for every regression method. This reveals that raster cells with a high coverage of settlement and forest area are especially prone to harbor forest clearances or that for raster cells with a lot of settlement area, there is an increased probability for forest clearances with increasing forest area and vice versa. In raster cells without forest area (according to the land-use statistic), in the Jura and the Plateau, there is a clear tendency for a U-shaped effect of the settlement area ($ca1 + ca1^2$) on the probability for forest clearances. This does not apply for the Prealps, where the settlement area has no statistically significant effect at all. The Alps and the Southern Alps, however, show a noteworthy pattern. There, only the linearized GMM spatial logit estimates support the U-shape, whereas the logit and robust logit models rather indicate an inverted U-shape. In raster cells without settlement area, in the Jura, the forest area ($ca3 + ca3^2$) seems to have about no effect on the probability for forest clearances, whereas in the Plateau and in the Prealps, the estimates clearly indicate statistically significant U-shaped effects across the regression methods. In the Alps and Southern Alps, for the forest area, we find a similar pattern as with the settlement area. The linearized GMM spatial logit models support the U-shaped effect, while the logit and robust logit models do not.

The unproductive area (ca4), as it is especially common on high elevations in the Alps, not surprisingly tends to have a negative effect on the probability for forest clearances. In the Jura, unproductive area clearly has no effect. In the Plateau, it has a statistically significant negative effect, and the same is true for the Alps. In the Prealps, only the logit and robust logit models find a statistically significant negative effect of this land-use type on forest clearances. In the Southern Alps, it is the other way around, only the linearized GMM spatial logit models support the negative effect.

The joint entropy (joinent) has an overall statistically significant positive effect on the probability for forest clearances, except the estimates of the logit and robust logit models in the Southern Alps. Because of the interaction between slope and the joint entropy (slope*joinent), the estimates for the joint entropy (joinent) only measure the effect on the probability for forest clearances for flat raster cells ($slope = 0$). The joint entropy is an information theory-based complexity or uncertainty metric. It is inversely proportional to contagion or clumpiness. Higher values correspond to a higher landscape (or rather land-use) complexity (Nowosad and Stepinski, 2019). Hence, in flat terrain, an increasing land-use complexity leads to a higher probability for forest clearances.

The interaction between slope and the joint entropy (slope*joinent) reveals an interesting pattern across the different regions. In the Jura and in the Plateau, we find a statistically significant negative effect. Thus, the probability for forest clearances diminishes with steeper slopes and higher land-use complexity. In the Prealps, the pattern starts to shift, the estimates are smaller and some are not statistically significant anymore. In the Alps, only the linearized GMM spatial logit models with a neighborhood radius of 10 km are statistically significant. The sign, however, changed to a positive effect. In the Southern Alps, the estimates are higher, but only for the linearized GMM spatial logit models clearly statistically significant. It looks like the interaction effect between slope and the joint entropy changes its sign from North to South. Especially in the Southern Alps, steeper slopes with high land-use complexity exhibit a higher probability for forest clearances.

To compare effect sizes, Fig. 3 provides an overview of the standardized coefficients across variables, regions and regression methods. It shows that the land-use related factors prove to be important contributors to forest clearances. In the Southern Alps, due to a greater uncertainty corresponding to wider confidence intervals, the effects of some variables seem to be larger than in the remainder of the country. The socio-economic factors seem not to have relevant effect sizes. Only in the Jura, the negative effect of the total population size in 2017 (B17TOT) is noticeable. When it comes to the predisposing environmental factors, TPI and the distance to waters show smaller effect sizes compared to altitude and slope. The greatest effect sizes but also the greatest uncertainty is to be found in the land-use related factors. Despite exhibiting the most statistically significant estimates, the interaction between settlement and forest area (ca1*ca3) shows the smallest effect sizes within the land-use related variables. The effects of the forest area ($ca3 + ca3^2$) are a bit more pronounced in magnitude than the effects of the settlement area ($ca1 + ca1^2$). Whereas the effect of the unproductive area (ca4) is most of all relevant in the Alps and Southern Alps. The joint entropy (joinent), finally, has a greater effect size than the interaction between slope and the joint entropy (slope*-joinent). Thus, the effect of land-use complexity is more pronounced in flat regions.

In the linearized GMM spatial logit models, an additional parameter is estimated, namely the spatial lag parameter (ρ). Fig. 4 gives an overview of the ρ coefficients and their corresponding confidence intervals, across the four different spatial regression models and the five forest regions. With the exception of the Southern Alps, we find strong evidence for the clustering of forest clearances in space. The patterns of spatial autocorrelation were statistically significant, positive and close to 1. Hence, forest clearance locations tend to be close to other forest clearances. Also here, for the Plateau, Prealps, and Alps, the models with $\alpha = 1$ and $r = 10$ km considerably deviate to the left. For the Prealps, the deviation is even indicating spatially dispersed (and not clustered) forest clearances ($\rho < 0$). Although there is some visual indication of clearance clusters in the Southern Alps (Fig. 1), surprisingly, no statistically significant spatial autocorrelation was found. This unexpected finding might be due to the observed greater uncertainty (wider confidence intervals) in respect to some variables in the Southern Alps.

4. Discussion & conclusion

This paper extends the analysis of drivers of forest clearances by a new perspective, namely that of Switzerland as a non-tropical and non-developing country, while at the same time also accounting for the frequently ignored spatial autocorrelation. The comparison of statistical significance and importance of the variables as well as different spatial and non-spatial regression methods across regions helped not only to uncover patterns but also to judge the sensitivity, reliability and relevance of our findings. In the following, we discuss our results in the light of the variable importance, and with an emphasis on differences across regression methods, then we discuss limitations of the study and offer conclusions.

We observe that land-use related factors are valuable predictors for forest clearances, followed by the effects of the predisposing environmental factors, while the effects of the socio-economic factors turned out to be very small. Unfortunately, there are hardly any other studies on

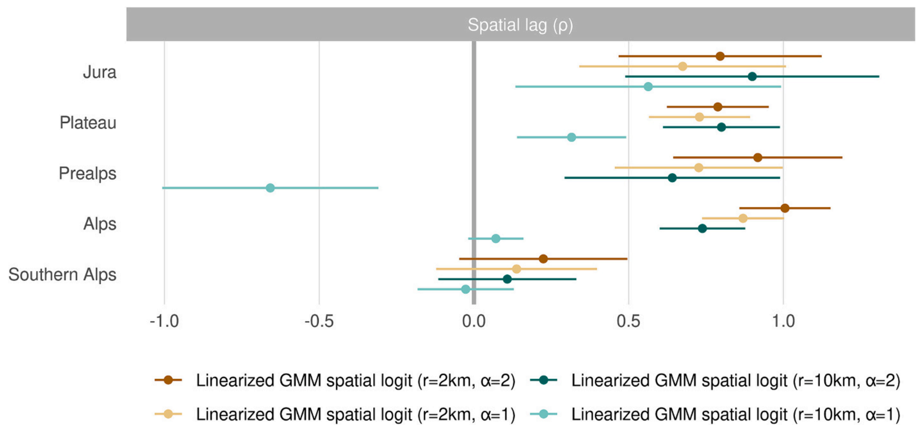

Fig. 4. Spatial lag parameters (ρ) estimated using linearized GMM spatial logit models.

drivers of deforestation that contrast the statistical significance with a comparable measure of variable importance. In related machine learning based literature, however, variable importance is often reported, but the functional forms how variables affect the outcome remain unclear. Also, landscape metrics are very rarely used in the literature on drivers of deforestation. Hence, it is difficult to compare our results with others. Analogously, Loran et al. (2017) found low correlation between socio-economic factors and forest loss in Switzerland, as well as a stronger impact of predisposing environmental factors than socio-economic factors, however, on forest expansion (Loran et al., 2017). In general, predisposing environmental factors show more consistent associations with deforestation, while socio-economic factors are more uncertain and show differing ones (Busch and Ferretti-Gallon, 2017).

We found a U-shaped effect on the probability for forest clearances (1) for forest area in raster cells without settlement area, and (2) for settlement area in raster cells without forest area (according to land-use statistic). Hence, with an increasing settlement or forest area, the probability for forest clearances first decreases, then increases again. These effects are especially clear in the Swiss Plateau. The probability for forest clearances increases with an increasing settlement as well as forest area. This interaction effect, although highly significant, turned out to be moderate in effect size. In the Alps and in the Southern Alps, unproductive area exhibits a negative effect on the probability for forest clearances.

In flat areas, a higher land-use complexity (joint entropy) generally comes with an increased probability for forest clearances, while in uniform landscapes, i.e., when the joint entropy is zero, increasing slopes decrease the probability for forest clearances in the Alps and Southern Alps but increase it in the Prealps. Increasing slopes together with land-use complexity rather decreases the clearance probability, except in the Southern Alps and Alps, where an increased probability can be observed.

Within the group of land-use related factors, surprisingly, variables related to agricultural area and waters (lakes and streams) had no explanatory power and thus were dropped from the analysis model. Agricultural variables in Switzerland seem only to influence the expansion of forest area (land abandonment, etc.) (Baur et al., 2006; Hirschi et al., 2012), but not forest clearances. This is not a surprise insofar as it only confirms that due to the legal framework conditions in Switzerland, agriculture is completely excluded as a reason for forest clearances. In the future, however, agriculture-related variables may gain some explanatory power because of the increased policy measures to protect agricultural land, especially crop rotation areas (GPK-N, 2021).

A meta-analysis on deforestation drivers (Busch and Ferretti-Gallon, 2017), based on 101 studies, found a consistent negative effect for altitude and slope. In strong contrast to those studies, we found that (1) altitude in the Alps, and (2) slope in the Prealps had a positive effect on forest clearances. However, because of the interaction with the joint entropy, slope is not directly comparable. Clearances for infrastructure for winter tourism, reservoirs and energy in the Alps could explain that finding. Further, Busch and Ferretti-Gallon (2017) also identified a consistent positive effect of population on deforestation, where we indeed found a rather negative effect of population, although with a small effect size. Hence, in Switzerland, clearances tend to be located in areas with lower population densities.

Our results show that estimates as well as their confidence intervals often differ between logit and robust logit models. For example, statistically significant effects found with the logit model turned out to be not statistically significant using the robust logit model. By virtue of their design, estimates of robust logit models are more reliable (Wilcox, 2022). Unfortunately, robust methods are not yet widely used in the literature on drivers of deforestation, nor can they account for spatial autocorrelation. Disregarding this may lead to false conclusions and false recommendations (Ward and Gleditsch, 2019).

Literature is suggesting that the traditional assumption of independence between observations is often violated in statistical modelling with spatially distributed units (e.g. forest clearances). Spatial autocorrelation leads to underestimated standard errors. Weakly significant parameters may therefore actually be not statistically significant at all. Hence, estimates of regression methods that can account for spatial autocorrelation can be considered superior (Elhorst, 2014; Ferrer Velasco et al., 2020; Ward and Gleditsch, 2019). Indeed, we found such cases for example for the variable altitude. It happened that, in strong contrast to the other methods, the linearized GMM spatial logit estimates found no statistically significant effects. Using only non-spatial methods, such effects would have not only been overestimated, but even erroneously identified. Even worse, especially in the Alps, there were statistically significant estimates that even changed their sign and thus the entire direction of the effect across different regression methods.

For the linearized GMM spatial logit models, the choice of the radii of the neighborhood matrices plays a role most of all in the Alps. There are even some cases where the choice of the radius determines the statistical significance. It can be assumed that the larger radius of the neighborhood matrices provides more accurate estimates. This is because it includes more neighboring values and can thus correct for more extensive spatial autocorrelation.

The choice of the weighting factor α plays a crucial role for the regression estimates, especially in the Alps, and for some variables, e.g. altitude. The linearized GMM spatial logit models with a weighting factor $\alpha = 1$ (especially those with a neighborhood radius $r = 10$ km) yield estimates which almost can be considered outliers. Furthermore, what particularly sows doubt about the reliability of estimates derived using a weighting matrix with $\alpha = 1$ is that our sensitivity analysis revealed that by increasing the radius of the neighborhood matrices beyond 10 km, it was possible to considerably inflate the effect sizes for a few variables. Hence, the assumption that the weighting decreases faster with increasing distance ($\alpha = 2$), seems more reasonable and yields more reliable results, and thus the estimates for $\alpha = 2$ deserve far more confidence.

The true estimates lie probably somewhere between the robust logit model estimates and the linearized GMM spatial logit models with weighting factor $\alpha = 2$ and a radius of the neighborhood matrix of $r = 10$ km. It is certainly valuable to have the range of estimates of the various methods demonstrated. Furthermore, since spatial autocorrelation may be expected in the vast majority of spatial data sets, it certainly makes sense to use spatial regression models, even though they may be somewhat more complicated and slower.

With the exception of the Southern Alps, we find statistically significant positive spatial lag parameters (ρ). Hence, there is evidence of a pronounced clustering of forest clearances. Because of the estimated strong spatial autocorrelaton, this also acts as an objective additional justification for using spatial regression methods. In linearized GMM spatial logit models, and in contrast to the inefficient non-linearized GMM models, spatial lag parameters (ρ) over 0.5 can be expected to be slightly biased upward (Klier and McMillen, 2008). This, however, does not really affect the interpretation of the models. Unfortunately, it cannot be directly determined whether forest clearances are more easily authorized if other clearances have already been carried out in the immediate vicinity, or whether clusters are simply the result of their spatial suitability.

Finally, considering that some raster cells accommodate more than one coordinate of forest clearances, instead of presence/absence (logit) models, count data models (Willibald et al., 2019) could have yielded revealing findings. This, however, could also have led to incorrect results, as for more complex clearance projects sometimes only centroid coordinates were registered and not always all individual sites.

Forests provide a multitude of ecosystem services to society (Stritih et al., 2021; Sutherland et al., 2016) and safeguarding these services is a main rational for Switzerland's strict forest protection. Since land search for infrastructure development is continuously becoming more difficult in Switzerland, also due to improved protection of agricultural land, it can be assumed that the opportunity cost of using forest land may be the lowest. However, our analysis found no evidence that there are systematic patterns pointing in this direction. We interpret the lack of fully clear and cross-regional effects as an indication that forest clearance permits in Switzerland in fact are only granted in exceptional cases.

As the pressure from infrastructure on forests will undoubtedly increase in future (EEA, 2016), it is important to provide knowledge about the drivers of forest clearances as a basis for future policy making and to provide data driven findings in the debate on competing land-use options and potential reforms of the Swiss forest clearance ban. Our findings show that there is a high heterogeneity in the factors across regions which calls for spatially differentiated policy development.

CRediT authorship contribution statement

David Troxler: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing – original draft, Visualization. **Astrid Zabel:** Conceptualization, Methodology, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Adrienne Grêt-Regamey:** Conceptualization, Writing – review & editing, Supervision.

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.

Data availability

The authors do not have permission to share data.

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