

# Filling the European blank spot—Swiss soil erodibility assessment with topsoil samples

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## Abstract

Soil erodibility, commonly expressed as the K-factor in USLE-type erosion models, is a crucial parameter for determining soil loss rates. However, a national soil erodibility map based on measured soil properties did so far not exist for Switzerland. As an EU non-member state, Switzerland was not included in previous soil mapping programs such as the Land Use/Cover Area frame Survey (LUCAS). However, in 2015 Switzerland joined the LUCAS soil sampling program and extended the topsoil sampling to mountainous regions higher 1500 m asl for the first time in Europe. Based on this soil property dataset we developed a K-factor map for Switzerland to close the gap in soil erodibility mapping in Central Europe. The K-factor calculation is based on a nomograph that relates soil erodibility to data of soil texture, organic matter content, soil structure, and permeability. We used 160 Swiss LUCAS topsoil samples below 1500 m asl and added in an additional campaign 39 samples above 1500 m asl. In order to allow for a smooth interpolation in context of the neighboring regions, additional 1638 LUCAS samples of adjacent countries were considered. Point calculations of K-factors were spatially interpolated by Cubist Regression and Multilevel B-Splines. Environmental features (vegetation index, reflectance data, terrain, and location features) that explain the spatial distribution of soil erodibility were included as covariates. The Cubist Regression approach performed well with an RMSE of 0.0048 t ha h ha<sup>-1</sup> MJ<sup>-1</sup> mm<sup>-1</sup>. Mean soil erodibility for Switzerland was calculated as 0.0327 t ha h ha<sup>-1</sup> MJ<sup>-1</sup> mm<sup>-1</sup> with a standard deviation of 0.0044 t ha h ha<sup>-1</sup> MJ<sup>-1</sup> mm<sup>-1</sup>. The incorporation of stone cover reduces soil erodibility by 8.2%. The proposed Swiss erodibility map based on measured soil data including mountain soils was compared to an extrapolated map without measured soil data, the latter overestimating erodibility in mountain regions (by 6.3%) and underestimating in valleys (by 2.5%). The K-factor map is of high relevance not only for the soil erosion risk of Switzerland with a particular emphasis on the mountainous regions but also has an intrinsic value of its own for specific land use decisions, soil and land suitability and soil protection.

**Key words:** cubist regression / digital soil mapping / erodibility / LUCAS / RUSLE / soil erosion / soil properties

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## 1 Introduction

The productive capacity of the soil is the most important resource for human food supply (Morgan, 2006; Borrelli et al., 2017). However, depletion in productive capacity and an increase of soil erosion rates are progressing with the growth of population and agricultural intensification (Brown, 1981; Pimentel et al., 1995; Lal, 2001; Yang et al., 2003; Dotterweich, 2013). On global arable lands, soils are not in equilibrium as soil loss rates exceed the tolerable soil loss (FAO, 2015). Among the physical parameters influencing soil erosion (soil physical, chemical, and biological properties, climate conditions, landscape characteristics; Verheijen et al., 2009) the susceptibility of soil is controlled by soil properties that restrain the detachment of soil particles, and affect infiltration, permeability, and water capacity (Wischmeier and Smith, 1965).

The susceptibility of a soil to erode is commonly called soil erodibility. It is assessed as the K-factor in the Universal Soil Loss Equation (USLE; Wischmeier and Smith, 1965) and its revised versions (RUSLE; Renard et al., 1997) which compute soil erosion by a multiplication of the rainfall erosivity R, cover and management C, slope length and steepness LS, and support practices P (Wischmeier and Smith, 1978). Experimentally, the K-factor is the average annual soil loss (A) per rainfall erosivity unit (R) measured for the standard conditions of the unit plot (Wischmeier and Smith, 1978):

$$K = \frac{A}{R} \quad (1)$$

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In a rather practical context, it can be seen as a value to describe the annual average of the total soil and soil profile reactions in relation to substantial water erosion processes like detachment and transport (Renard et al., 2010). Information about soil erodibility is preferable to be assessed by long-term measurements on natural plots (Renard et al., 2010). A relationship of soil erodibility and particle size distribution was assessed by Wischmeier et al. (1971) for soils in the USA and expressed in a nomograph. That nomograph was developed to estimate soil erodibility from readily available soil property data and standard profile descriptions as field measurements of K are time-consuming and demand at least 3 (up to 10) years of measurement to determine values (Foster et al., 2008). Later, Wischmeier and Smith (1978) developed an equation that rests on the nomograph based on rainfall simulations data from 55 soils in the US [see Eq. (2); Renard and Ferreira, 1993]. This equation is the most used and cited function to calculate soil erodibility from ready-to-use soil data (Borrelli et al., 2017). Alternative equations for particular soil types (e.g., high clayey, volcanic, mollisol) were developed, but these are not of necessity for Swiss conditions (Wang et al., 2013). Auerswald et al. (2014) developed a K-factor equation based on German soil survey data. Their equation fully emulated the nomograph of Wischmeier and Smith (1978) beyond the limitations of 70% silt, soil erodibility less than 0.02 t ha h ha<sup>-1</sup> MJ<sup>-1</sup> mm<sup>-1</sup>, 4% soil organic matter, and exclusion of rock fragments. However, the equation is not yet widely tested (applied in 5 publications) and considered as “far from perfect in many cases” (Auerswald et al., 2014). To ensure a continental comparability of Swiss soil erodibility, we decided to use the equation of Wischmeier and Smith (1978), which was earlier applied for European countries (see below; Panagos et al., 2014).

Determining the soil properties of the equation of Wischmeier and Smith (1978) includes topsoil texture (sand, very fine sand, silt, and clay content), soil organic matter, soil structure, and soil permeability (Wischmeier et al., 1971). However, as the latter parameters are also difficult to measure, and regarding the demand on large-scale models and assessments, alternative methods to cover the spatial distribution of soil information are needed (Diek et al., 2016; 2017; Wang et al., 2016a). Still the majority of these alternatives follow the nomograph or equation of Wischmeier et al. (1971) and Wischmeier and Smith (1978) to model soil erodibility with soil properties derived by remote sensing (Wang et al., 2016b; Ostovari et al., 2017) or digital soil mapping (DSM) techniques (Bahrawi et al., 2016; Ganasri and Ramesh, 2016; laaich et al., 2016).

For Switzerland, previous studies have used a variety of polygon-based soil property and soil suitability maps of different scales to estimate the soil erodibility based on the parameter classes of texture, stone, and organic matter content (Prasuhn et al., 2010; 2013). Unfortunately, high- and medium-resolution soil maps (up to 1:50000) are heterogeneous and do only cover 25% of the Swiss national area. With the recent demand of national spatial soil data, DSM evolved as an appropriate method to complement the conventional soil survey methods (McBratney et al., 2003) that are often biased especially for Switzerland with its high percentage of

remote mountain areas with low accessibility (Nussbaum et al., 2014; 2017; 2018). The principle of DSM considers that similar environmental conditions cause the formation of similar soil and soil properties (Hudson, 1992).

Often, soil survey input data sources of the DSM maps originate from non-uniform soil databases, which make the results often incomparable, although underlying equations and methodologies are identical. Topsoil surveys (0–20 cm) in the framework of the Land Use/Cover Area frame Survey (LUCAS; Tóth et al., 2013) allowed the establishment of a homogenous soil database across 23 EU member states. Panagos et al. (2012a) presented a K-factor map as a first homogenized product of the database. Later, the underlying spatial prediction methodology was improved (Cubist Regression and Multilevel B-Splines), the number of soil samples increased and the number of countries enlarged (25 EU member states; Panagos et al., 2014). The past two sampling campaigns of LUCAS (2009–2012 and 2015) cover a total of more than 22,000 soil samples (Orgiazzi et al., 2018). As Switzerland was not part of the first LUCAS sampling (2009), an extrapolation of soil erodibility for Switzerland without Swiss soil samples was realized based on topsoil data of other EU countries (map uploaded at the European Soil Data Centre ESDAC; Panagos et al., 2012b). However, this extrapolated soil erodibility is associated with high uncertainties and was therefore not published in a peer-review journal. In 2015, Switzerland joined the LUCAS program and 199 samples were collected. For the first time also soil samples from mountain areas above 1500 m asl were included ( $n = 39$ ).

Although the presence of seasonal effects on the K-Factor (mainly triggered by freeze-thaw processes) is discussed in the literature (Renard et al., 1991; Renard and Ferreira, 1993; Renard et al., 1997; Bryan, 2000), we decided not to model soil erodibility on a seasonal scale. Kinnell (2010) reviewed different approaches to assess the seasonality of the K-factor. However, none of these approaches include the hardly measurable influencing interactions and effects (e.g., climate influences and seasonality of freeze-thaw, compaction by life stock trampling, human management activities) simultaneously for a proper process-oriented modeling (Leitinger et al., 2010; Piñeiro et al., 2010; Vannoppen et al., 2015). Furthermore, the divergence of seasonal K-factors to an annual K-factor is poorly discussed in the literature (e.g., Wall et al., 1988). In the RUSLE2 User's Reference Guide (Foster et al., 2008) it is even stated that no statistical evidence exists for an inconsistency of soil erodibility over time. Rather, the rainfall erosivity (Schmidt et al., 2016) and the cover and management factor (Schmidt et al., 2018) can be seen as highly dynamic erosion factors with an intra-annual variation.

The aim of the present study is to assess the spatial and temporal patterns of soil erodibility of Switzerland by (1) mapping K-factors based on Swiss LUCAS data. Additionally, (2) differences between the interpolation and extrapolation to produce a national soil erodibility map are evaluated. With the mapping of soil erodibility based on soil samples, we aim to improve the prediction of the existing extrapolated soil erodibility map.

## 2 Material and methods

### 2.1 LUCAS topsoil sampling

A dataset of 199 soil samples from the LUCAS topsoil sampling was used to obtain a soil erodibility map of Switzerland. The LUCAS topsoil sampling is a standardized procedure with one aliquot out of five mixed subsamples for each sampled location. A recent review about LUCAS is provided by Orgiazzi et al. (2018). All samples were air-dried and analyzed for particle size distribution (according to the USDA classification) and soil organic carbon content in a single ISO-certified laboratory. The laboratory analysis is explained in detail by Orgiazzi et al. (2018). 160 soil samples of Switzerland cover grasslands and forests at elevations less than 1500 m asl (sample distribution of 12.7 km × 12.7 km), 39 samples were taken at the same land use units in the Alpine region above 1500 m asl (20.6 km × 20.6 km) (named as Alpine samples throughout the study). The total Swiss sample set spans over elevations from 287 m asl to 2337 m asl. It covers all biogeographic regions (Jura, Alpine Midland, and Northern/Southern/Western/Eastern Alps) of Switzerland and has a mean point density of one per 207 km<sup>2</sup>, which equals an average distribution of one sample within a grid of 14.4 km × 14.4 km (Fig. 3). That sample spread of Switzerland corresponds to the mean spread across the 25 EU Member States of the 2009–2012 sampling (14 km × 14 km; Panagos et al., 2013). The Alpine samples were selected following a stratified random sampling to make sampling in remote areas possible. As a logistical stratum we selected sampling points at grassland locations above 1500 m asl by the criteria of accessibility (max. distance of 200 m to the next street accessible with 4-wheel drive). We tried to manually cover the natural strata exposition (south, north) and geological units (consolidated and unconsolidated sediment, igneous rock, metamorphic rock) which are related to the soil formation but are not homogeneously assessed by a random sampling approach. We assume that differently exposed soils experienced another degree of solar radiation (Yimer et al., 2006) and soil texture varies with geological units (Jenny, 1941). After assigning the strata, the 39 samples were randomly distributed (in ESRI ArcGIS) proportional to the strata units to cover each combination of exposition and geology. Additionally, 1638 samples of the surrounding countries Germany, Austria, Slovenia, Italy, and France were used to delineate a better prediction for the spatial interpolation (see below). These data were already part of the European soil erodibility mapping (Panagos et al., 2014). Additionally, the European Soil Database (King et al., 1994) provides information for the soil structure of the LUCAS samples.

### 2.2 Calculation of soil erodibility for the LUCAS topsoil samples

The soil erodibility (K) equation by Wischmeier and Smith (1978) includes the following soil properties: particle size distribution in percent [very fine sand  $m_{vfs}$  (0.05–0.1 mm), silt  $m_{silt}$  (0.002–0.05 mm), and clay  $m_{clay}$  (< 0.002 mm) content], the organic matter content OM in percent, the soil structure class s and the permeability class p. According to their empiri-

cal experiments, Wischmeier and Smith (1978) propose to calculate the soil erodibility as the following function, whereby K is expressed in t ha h ha<sup>-1</sup> MJ<sup>-1</sup> mm<sup>-1</sup> according to the International System of units (Foster et al., 1981):

$$K = \left[ (2.1 \times 10^{-4} \times M^{1.14} \times (12 - OM) + 3.25 \times (s - 2) + 2.5 \times (p - 3)) / 100 \right] \times 0.1317, \quad (2)$$

where  $M$  is the textural factor composed of  $(m_{silt} + m_{vfs}) \times (100 - m_{clay})$ . The particle size distribution is analytically determined. Textural classes are set according to USDA (1951). Soil structure is defined as the overall architecture of soils and the assembling of individual texture components like sand, silt, and clay and its combination to aggregates (Chesworth, 2008). It can be derived by a pedotransfer function including the land use class and soil name proposed by van Rast et al. (1995). Soil structure is classified into four classes: humic, poor, normal or good. Soil permeability is the soils capacity to transmit water and can be assessed by the soil texture classes (permeability classes 0 to 4) (USDA, 1983; Chesworth, 2008). The used tables to extract soil structure s and soil permeability p can be found in Panagos et al. (2014). The soil erodibility equation underlies three restrictions: silt content > 70% is set to 70%, organic matter content > 4% is set to 4%, and the very fine sand fraction is estimated as 20% of the total sand fraction (Panagos et al., 2014). Only 1 out of 199 of all Swiss samples (0.5%) has a silt fraction greater 70% and was adjusted to that threshold. Assets and drawbacks of the organic content limitation are already discussed (Panagos et al., 2014). The fine sand fraction was approximated to 20% of the total sand fraction (Panagos et al., 2014). A particle size analysis of a subset of the Swiss samples ( $n = 38$ ) including very fine sand (26% of total sand) confirmed that an estimated ratio of 20% is appropriate for European soils.

Additionally, we calculated the K-factor for all 199 Swiss LUCAS topsoil samples based on another K-factor equation proposed by Römken et al. (1997), which takes only the soil texture into consideration and neglects the soil organic matter content, the soil structure, and the soil permeability. The information on soil texture is transformed by the geometric mean particle diameter equation by Shirazi and Boersma (1984).

As discussed in the literature (Poesen et al., 1994; de Figueiredo and Poesen, 1998; Panagos et al., 2014; Bosco et al., 2015), the positive effects of the stone cover on reducing soil erosion are not negligible. That impact can be incorporated into the soil erodibility calculation by using a correction factor  $S_t$  for the relative decrease in sediment yield. That correction factor is multiplied with the K-factor and calculated as following (Poesen et al., 1994):

$$S_t = e^{-0.04 \times (R_c - 10)}, \quad (3)$$

where  $R_c$  is the percentage of stone cover (stoniness). It was estimated (classes: 0–10%, ≥ 10–25%, ≥ 25–50%, ≥ 50%;



Eurostat, 2009) during the LUCAS topsoil sampling for each location (Panagos et al., 2014).

The soil erodibility K and soil erodibility incorporating the stoniness correction factor  $K_{st}$  were calculated for a total of 1837 LUCAS topsoil samples (including data from bordering countries in addition to the 199 Swiss samples) following the Eqs. (2) and (3).

### 2.3 Mapping the K-factor for Switzerland

In the present study we used vegetation indices (Normalized Difference Vegetation Index NDVI, Enhanced Vegetation Index EVI) of the Moderate Resolution Imaging Spectroradiometer (MODIS) data MOD13Q1 (Didan et al., 2015), reflectance data from MODIS, terrain features (elevation, slope, base level of streams, altitude above channel base level, and multi-resolution index of valley bottom flatness) derived from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (Farr et al., 2007), and latitude and longitude as covariates. A list of covariates can be found in Tab. 1 and in Panagos et al. (2014). These covariates are already identified as the most important for predicting soil erodibility in the European Union. In order to be reproducible, consistent, and comparable we used the same predictive variables and resolutions for Switzerland as were used for the European Union.

We used Cubist Regression (CR) (Quinlan, 1992; 1993) to spatially predict the K-factors for Switzerland including the above-mentioned covariates. CR is a tree model that uses recursive partitioning to subset the dataset into finer rule-based sub-datasets. These rules cluster data with relatively homogeneous characteristics. As long as a condition is identified to be false, the model proceeds with the next rule until it meets a true condition. As soon as a situation matches a condition, an individual linear regression model is fit for the data partition. A specific set of covariates that predict best is automatically chosen for each subset of an individual regression equation (Ballabio et al., 2017). It can be seen as a model tree with linear regression models at its terminal leaves. As such, CR allocates a series of local linear regression models and results in an overall combined non-linear function. Furthermore, it makes use of the previous linear regression to smooth and adjust the prediction (prevent underprediction, reduce overfitting). The selection of covariates and combina-

tion of regressions increase the estimation accuracy. After the CR, the residuals are interpolated with Multilevel B-Splines (MBS) (Lee et al., 1997). MBS interpolate scattered points to generate a smooth surface as well as the best fit of these points. The method used a hierarchy of control lattices to generate a series of functions, whose sum approaches the desired approximation function (Weis and Lewis, 2001). A bootstrapped cross-validation (Efron and Gong, 1983) (100 repetitions) with randomly selected samples and a one out of ten replacement of the main dataset was used to fit the model. The  $K_{st}$ -factor, incorporating the effect of stoniness, was also modeled by CR and MBS. The modeling was performed in R (v 3.4.2) with the packages 'cubist' and 'MBA'. Terrain features were extracted in SAGA GIS (v 6.0.0) (Conrad et al., 2015) and visualization was realized in ESRI ArcGIS (v 10.3.1).

The K- and  $K_{st}$ -factor values are the base for the DSM. We extended the database across the Swiss border to increase population size for the statistical regressions, to better predict particularly the border areas of Switzerland and the special features of the high Alpine soils erodibility where the sample number is limited.

The performance of the interpolation is evaluated with the standardized measure of certainty  $f$  based on the standard deviation  $s$  of the estimated variable  $V$  (McBratney et al., 2003) and calculated as follows:

$$f = 1 - \min\left(\frac{2s}{V}, 1\right). \quad (4)$$

A low certainty is expressed by 0 (0%) and high certainty by 1 (100%).

### 2.4 Extrapolation of soil erodibility for Switzerland by using data from EU countries

Extrapolated K-factor maps for European countries (from the EU28 assessment; Panagos et al., 2013) not being part of the previous LUCAS campaigns are already provided via the European Soil Data Centre (Panagos et al., 2012b; ESDAC, 2018) due to a number of requests from non-EU users. The extrapolated map of Switzerland used the same covariates and methodology but is not supported by measured data. A

**Table 1:** List of covariates used in the cubist regression model for modeling the soil erodibility of Switzerland.

Covariate group	Covariate	Spatial resolution	Data source
Vegetation index	Normalized Difference Vegetation Index NDVI, Enhanced Vegetation Index EVI	250 m	Moderate Resolution Imaging Spectroradiometer (MODIS) MOD13Q1 (Didan et al., 2015)
MODIS raw band data	Band 1, 2, 3, 7	250 m	MODIS (Didan et al., 2015)
Terrain features	elevation, slope, base level of streams, altitude above channel base level, multi-resolution index of valley bottom flatness	25 m	Shuttle Radar Topography Mission (SRTM) (Farr et al., 2007)
Location parameter	latitude, longitude		

comparison of the extrapolated map with the herein processed interpolated K-factor map of Switzerland evaluates the necessity for soil input data into the DSM process.

### 3 Results and discussion

#### 3.1 Soil properties and erodibility of the LUCAS topsoil samples

The calculations of the K factor from the analysis of the 199 Swiss LUCAS topsoil samples in the laboratory show an average soil erodibility of  $0.0334 \text{ t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$  (Tab. 2) with a range from  $0.0180 \text{ t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$  (lowest susceptibility of Swiss soils to be eroded) to  $0.0611 \text{ t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$  (highest susceptibility of Swiss soils to be eroded). 83% (166) of all samples have K-factor values between  $0.0250 \text{ t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$  and  $0.0400 \text{ t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$ . The K-factor increases as the samples are getting siltier (Spearman correlation coefficient  $r_s = 0.397$ ). Silt content varies between 16% and 73%. The mean fraction of very fine sand is 6.4% (range from 1.2% to 16.4%). A higher content of the sand fraction is very weakly correlated with a reduction of the K-value ( $r_s = -0.078$ ). The mean clay content of all 199 samples is 17.7% (range from 2.0% to 40.0%). All samples are rich in organic matter content with a mean proportion of 3.3%. Erodibility is slightly reduced by a higher content of organic matter ( $r_s = -0.265$ ). However, in general, *Wischmeier* and *Manning* (1969) could not identify a clear correlation between organic matter and soil erodibility as particle size distribution is overruling a possible influence.

Soil structure class has a relatively low variability in Switzerland. Only 1% of soil structure is classified outside class 1 or 2. The permeability class with the highest frequency is 3 (moderate). Soils with higher permeability have a higher infiltration capacity and reduce runoff. In a first approach, we con-

sidered a pedotransfer function to predict the soil permeability instead of deriving soil permeability from soil texture classes. As such, a subset of undisturbed topsoil samples of 11 Alpine locations with three replicates were measured in the laboratory according to the corresponding saturated hydraulic conductivity. Results indicated that the permeability was driven by secondary pores and not at all related to the primary porosity. That fact impedes the prediction and led us back to the original approach of *Panagos et al.* (2014).

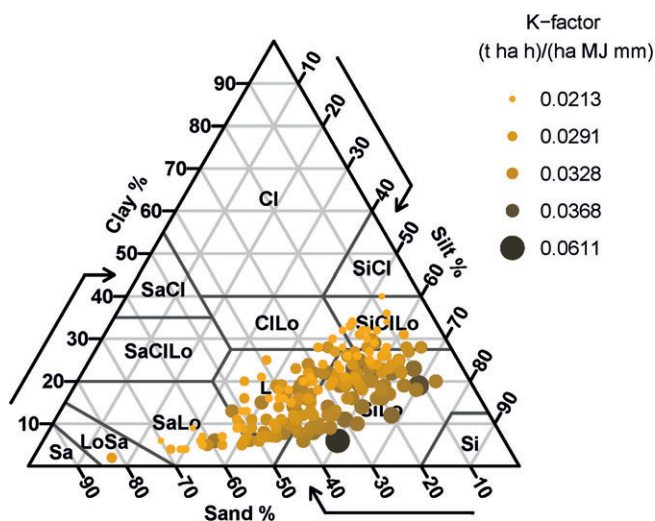
The 39 Alpine samples are rich in sand content and can be classified as loamy soils. The mean soil texture of the remaining 160 Swiss samples is silty loam. Most of the Swiss samples are either classified to the texture class loam or silty loam (Fig. 1). The mean soil erodibility of samples above 1500 m asl is smaller than the mean of locations below 1500 m asl ( $0.0320$  versus  $0.0338 \text{ t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$ , respectively), although a decreasing trend of clay content ( $r_s = -0.172$ ) with height and a slightly increasing trend of very fine sand and organic matter ( $r_s = 0.151$ , resp.  $r_s = 0.159$ ) with height (from 287 m asl to 2337 m asl of 199 samples) is observed. Spatial trends by latitude exist for clay and sand. Clay content increases ( $r_s = 0.545$ ) and sand content decreases ( $r_s = -0.476$ ) from South to North. This relation of latitude and soil properties is mainly influenced by the terrain contrasts between southern and northern Switzerland. No correlation exists between soil properties and longitude. We expected no relationship between soil properties and longitude as the terrain contrasts are heterogeneous and do not follow any obvious gradient. However, due to the correlation of soil properties and latitude we decided to use spatial coordinates as a predictor for the K-factor modeling in the following chapter.

The soil erodibility calculation based on *Römkens et al.* (1997) revealed a slightly different K-factor of  $0.0371 \text{ t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$ . However, we decided to use the nomograph based equation as it is recommended by *Renard et al.* (1997)

**Table 2:** Mean measured values for soil properties.

Soil properties	Samples		Switzerland
	< 1500 m asl	> 1500 m asl	
Number of samples n	160	39	199
Sand (%)	29.2	42.6	31.8
Very fine sand $m_{\text{vfs}}$ (%)	5.8	8.5	6.4
Silt $m_{\text{silt}}$ (%)	51.3	47.1	50.5
Clay $m_{\text{clay}}$ (%)	19.5	10.4	17.7
Textural factor M	4588.3	4965.4	4662.2
Organic matter OM (%)	5.3	5.9	5.4
Soil structure class $s^a$	1	1	1
Permeability class $p^a$	3	3	3
Soil erodibility K ( $\text{t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$ )	0.0338	0.0320	0.0334

<sup>a</sup>Mode value.



**Figure 1:** Particle size distribution diagram of all 199 LUCAS topsoil samples according to the USDA soil texture classification proportional to the K-factor (quantile classification).

as long as measured soil parameters are not limited and measured in the USDA soil texture classification.

## 3.2 Soil erodibility mapping

### 3.2.1 National soil erodibility map based on LUCAS topsoil samples

The mean spatially predicted soil erodibility for Switzerland is  $0.0327 \pm 0.0044 \text{ t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$ . The histogram represents a bell-shaped curve with varying K-factors from 0.0143 to  $0.0517 \text{ t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$ . Lowest values are in the Alpine valleys and highest in the top elevated regions of the Swiss Alps. The map has a spatial resolution of 500 m (Fig. 2; note that urban areas and lakes have been removed from the resulting Swiss K-factor map). The RMSE at all the 199 locations of predicted and measured samples is  $0.0048 \text{ t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$ . The standardized measure of certainty  $f$  is 87% for the predicted K values (Fig. 3). The distribution of certainties of predicted and observed K-factors is heterogeneous without any apparent distribution. The RMSE of all 1836 samples used for the spatial prediction (Switzerland incl. adjacent countries) is  $0.0064 \text{ t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$  with a mean predicted K of  $0.0328 \text{ t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$  and a  $f$  of 82%.

Advantages of CR are its capacity to work for non-linear relationships and its interpretability. It diminishes overfitting due to its partitioning and rule-based routines (Malone et al., 2017). Cubist is among the best performing prediction methods compared to 17 others (e.g., random forest, neural net, linear regression) (Kuhn and Johnson, 2013). MBS has a high performance in terms of computing speed and automatic optimization of the parameters. It was preferred over kriging, as kriging is heavily dependent on the variogram estimation, which can be problematic especially in computing the empirical variogram. The choice of binning distance, maximum range, and other parameters can drastically change the final

outcome. Moreover, kriging makes several assumptions about data distribution that are often not met in practice.

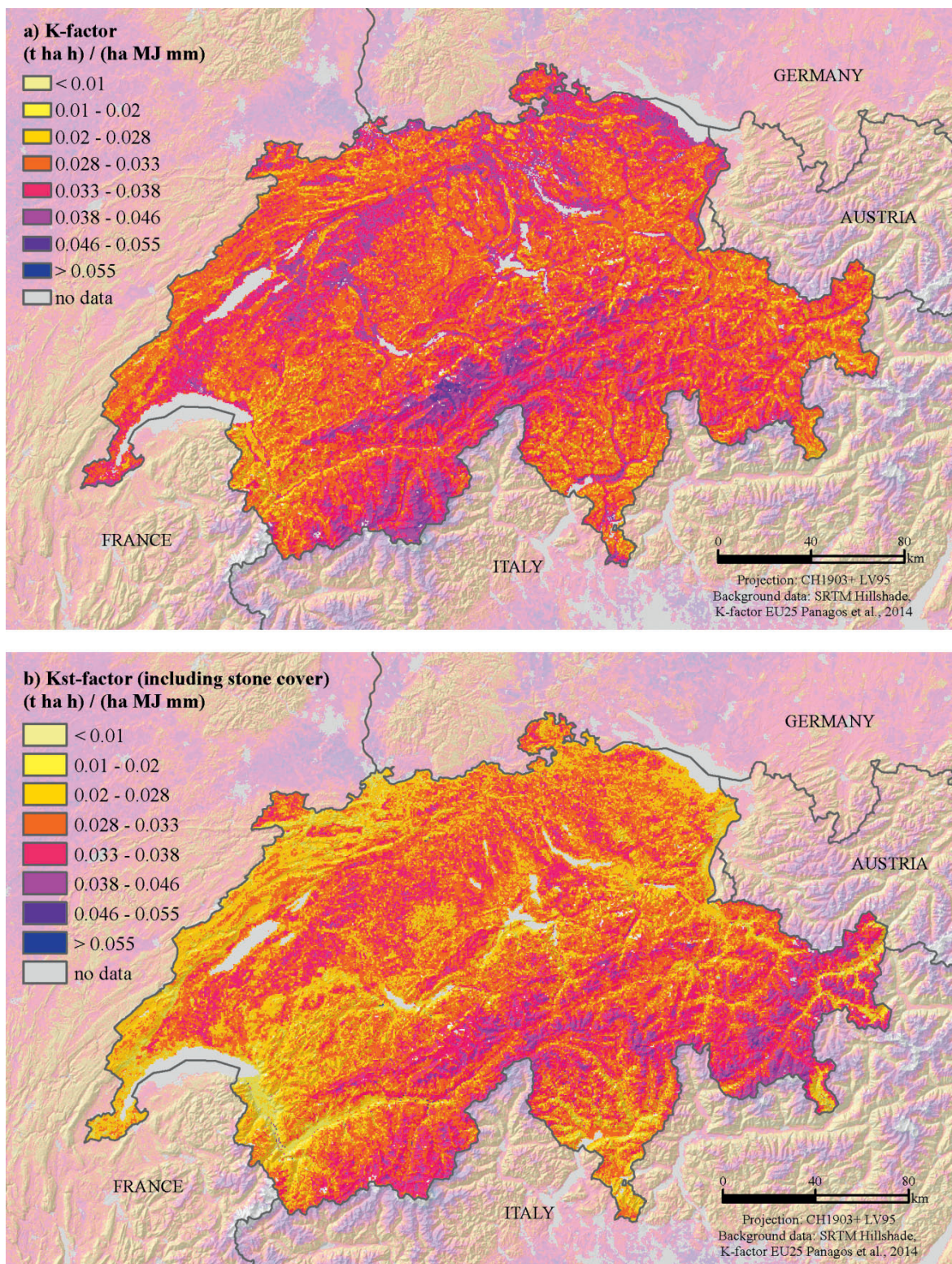
Vegetation indices, reflectance data, terrain features, and spatial coordinates were used as covariates. The relative importance of the used covariates is already discussed (Panagos et al., 2014). A direct relationship between the K-factor and hillslope features could be proved for mountainous areas of Southern Italy (Colombo et al., 2010). Kulikov et al. (2017) used terrain features (e.g., slope degree and curvature, elevation) next to Landsat band ratios as covariates to spatially model K-factors in Kyrgyzstan. According to a review by McBratney et al. (2003), the key sources of environmental covariates for predicting soil properties were either relief (80%) and/or auxiliary soil property (35%) data. Additionally, spatial coordinates appear to be serving as a meaningful predicting factor in DSM. They include spatial relationships which are not expressed in any other environmental variable (McBratney et al., 2003). Usually, parent material can be seen as a suitable covariate for soil erodibility as a relationship of the geological parent material and soil texture is often assumed (André and Anderson, 1961). However, our analysis on Alpine soils showed no significant correlation of geological bedrock and soil texture due to the homogeneous glacial till coverage (Blume et al., 2016) and the sampling only of topsoils.

Comparison of modeled K-factors for Switzerland and the surrounding countries reveal a mean of soil erodibility close to the averages of Austria ( $0.0321 \text{ t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$ ), Germany ( $0.0334 \text{ t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$ ), and Italy ( $0.0322 \text{ t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$ ). The K-factor of Slovenia is slightly lower ( $0.0313 \text{ t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$ ) with highest values in the karst zone (Prus et al., 2015). One exception is met by the comparison to France where the K-factor is higher ( $0.0356 \text{ t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$ ). The higher values in France might arise out of the high proportion of erodible loess plateaus in Northern France.

The average K-factors have a slightly positive altitudinal gradient (with the exception of the colline zone < 800 m asl). K-factors are increasing from  $0.0308 \text{ t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$  in the montane zone (800–1800 m asl) to a maximum of  $0.0404 \text{ t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$  in the nival zone (> 3100 m asl). Willen (1965) could identify a doubling of erodibility at elevation ranges of 2160 m asl compared to 600 m asl in California.

The incorporation of the stoniness cover reduces the spatially predicted mean K-factor of Switzerland by 8.2% (to  $0.0297 \text{ t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$  with a standard deviation of  $0.0054 \text{ t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$ ) (Fig. 2). This reduction is similar to the influence of stoniness in reducing K-factors in neighboring central European countries (Austria, Germany, and Slovenia). The RMSE ( $0.0054 \text{ t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$ ) is slightly higher,  $f$  is lower (83%) than those of the soil erodibility neglecting the stoniness effect. The strongest effect of stoniness to the soil erodibility is visible in the region close to the French border (Jura mountain range) and the northern Alpine foothill (Fig. 2). The reduction due to stone cover is smaller than the average reduction of the K-Factor at the European scale (15%; Panagos et al., 2014). The latter might be ex-



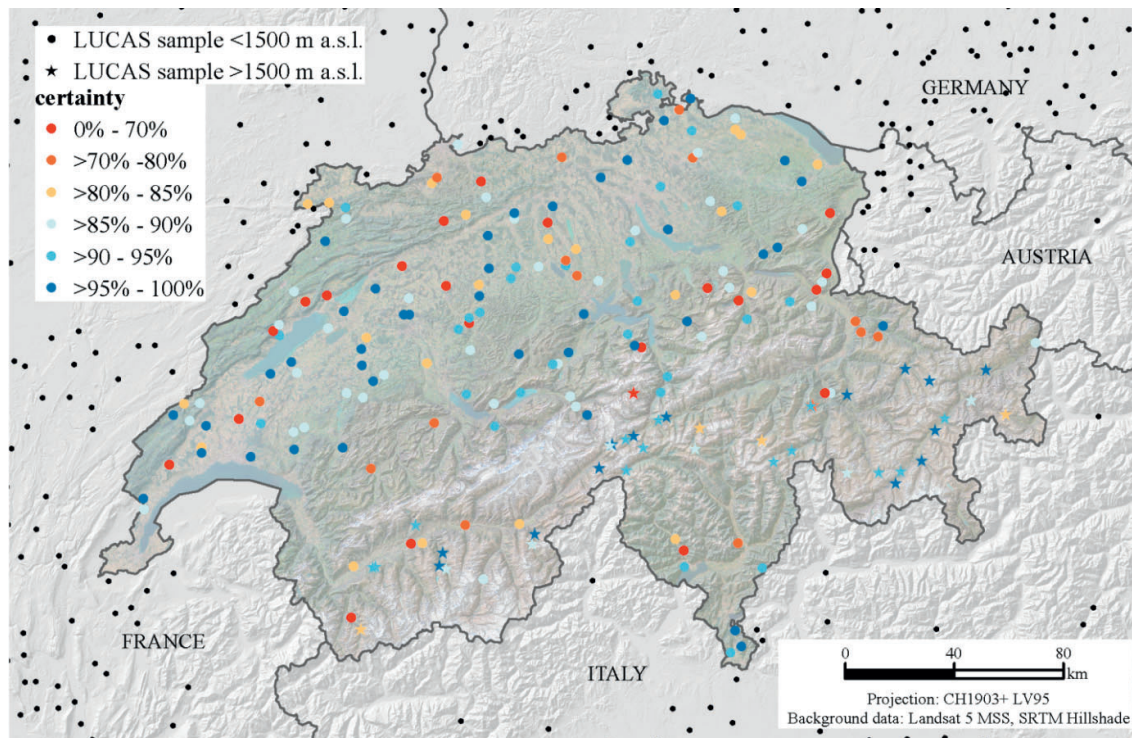


**Figure 2:** (a) K-factor and (b) K<sub>st</sub>-factor (including the effect of stone cover) maps of Switzerland.

plained by the relatively lower effect of stoniness in the high alpine regions of Switzerland compared to lowlands: the average K-factor in the Swiss lower regions (< 1500 m asl) is reduced by 12.2%, in the Swiss Alpine region (> 1500 m asl) only by 1.8%.

As auxiliary soil data, we considered datasets from Swiss federal agencies (e.g., NABODAT, Rehbein et al., 2017) and cantonal soil data. In these particular cases, we had to deal with inconsistencies owing to different soil sampling methods, sampling periods, laboratory analysis, clustered data, incom-





**Figure 3:** Certainty map of observed and predicted K-factor values of Switzerland in percentage (0% low certainty; 100% very high certainty) and distribution of LUCAS samples. Certainty is calculated according to Eq. (4). Black dots in the surrounding of Switzerland represent a subset ( $n = 261$ ) of the additional used 1638 LUCAS samples.

plete spatial coverage, and missing parameters. Thus, the tested local data could not be used to improve the model result.

### 3.2.2 Comparison with extrapolated mapping of soil erodibility at the European scale

The comparison of the extrapolated (EU map; no measured data for Switzerland available; Panagos et al., 2014) and the interpolated map (including measured data from Switzerland, this study) with identical methods (CR, MBS) and covariates results in similar average K-factor values for Switzerland ( $0.0327 \text{ t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$  vs.  $0.0333 \text{ t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$ ). The mean deviation of extrapolated and interpolated average values is  $-1.2\%$ . The mean is relatively balanced by considering under- and overestimation simultaneously. However, the spatial patterns, mainly caused by the addition of the measured Alpine samples that had not been integrated into the LUCAS before, expose some systematic deviations (Fig. 4).

The difference map shows an overestimation of K-factors in the top Alpine region and an underestimation in the valleys and Northern/Southern Alpine foothills by the extrapolated EU map compared to the interpolated map of this study. The highest overestimation can be found in the eastern Alps (Canton Grisons). The differences between extrapolation and interpolation of soil erodibility are relatively small in the lower relief Swiss midland in the north of the Alps, because these areas seem to be well represented by the non-Swiss LUCAS dataset. Regions with a small deviation ( $-6\%$  to  $8\%$ ) from the

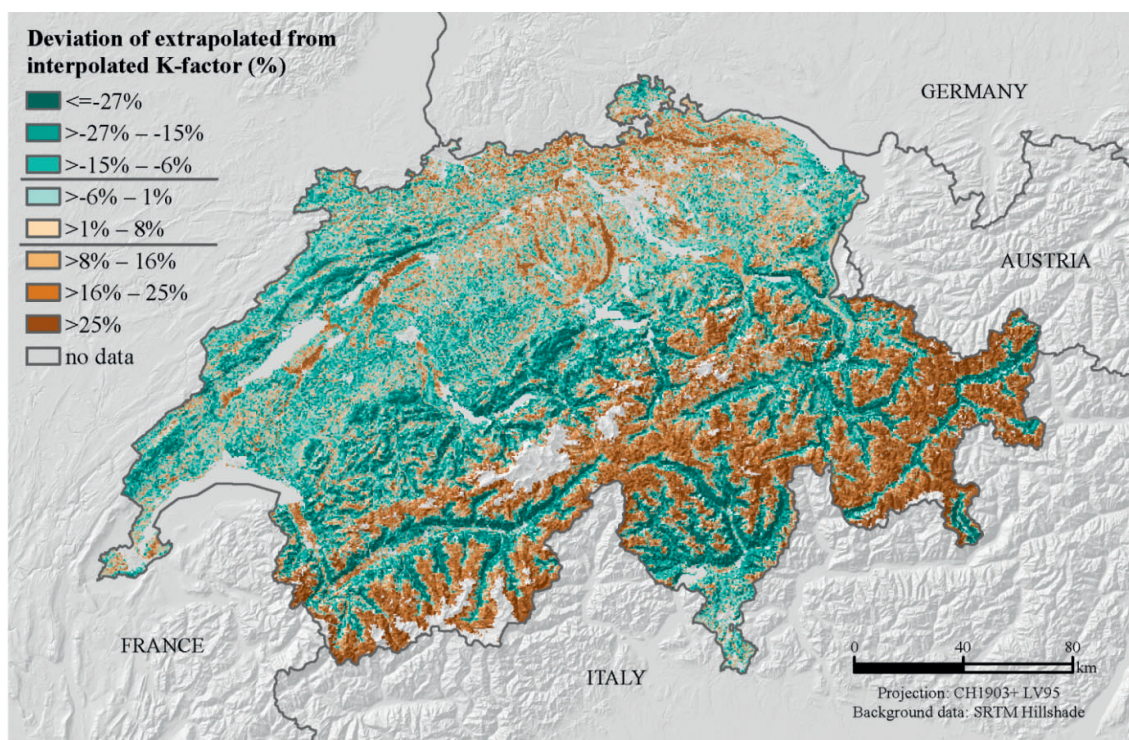
interpolated K-factor map have an average elevation of 272 m asl. The extrapolation is based on LUCAS topsoil samples of the surrounding EU countries and the sampling campaign was limited up to heights of 1500 m asl. This means that alpine samples were not considered in the extrapolation at all. Thus, neglecting of mountainous soils might provoke high uncertainties with a general trend of overestimating K-factors in the mountains. In contrast, even though lower regions like the Alpine valleys are included in the sampling of other countries were obviously nevertheless difficult to predict, most likely owing to the complex relief situations in Europe.

We calculated the local mean soil losses on a polygon scale over 100 random municipalities to evaluate the influence of an under-/or overestimate on the overall soil erosion risk assessment. The municipalities were derived from a total of 2382 Swiss municipalities of the dataset SwissBOUNDARIES3D (Swisstopo, 2018b). They are randomly distributed in Switzerland and are differently-sized (from  $1.2 \text{ km}^2$  to  $149.2 \text{ km}^2$ ). We used the annual R-, annual C-, and the LS-factor to multiply them once with the interpolated and once with the extrapolated annual K-factor of Switzerland. Results of the 100 municipalities showed a tendency of the extrapolated K-factors to overestimate soil loss by  $6.3\%$  and underestimate soil loss by  $2.5\%$  in the Alpine region ( $> 1500 \text{ m asl}$ ) and lower regions ( $< 1500 \text{ m asl}$ ), respectively.

## 4 Conclusions

The soil data of the Swiss soil erodibility mapping originates from the first LUCAS sampling campaign including samples





**Figure 4:** Difference of extrapolated K-factors (with no measured data from Switzerland) to the interpolated K-factors (based on 199 additional LUCAS topsoil samples in Switzerland) in percentages. Map classes are classified according to quantiles.

above 1500 m asl. For the first time, the K-factor based on measured topsoil samples is presented on a national scale in Switzerland. We modeled the spatial distribution of soil erodibility for Switzerland with Cubist Regression and Multilevel B-Splines under consideration of environmental covariates. An incorporation of the stoniness into the K-factor cover causes a mean reduction of 12.2% in the lower regions (< 1500 m asl) and 1.8% in the Alpine regions (> 1500 m asl). A comparison of the K-factors interpolated with 199 measured LUCAS topsoil samples in Switzerland (including  $n = 39 > 1500$  m asl) and extrapolated values based only on soil samples of the neighboring countries < 1500m asl of previous LUCAS campaigns not considering Switzerland, resulted in surprisingly consistent average values, but indicated considerable spatial deviations mostly at high elevations and in Alpine valleys. The analysis demonstrates that regions with high elevation contrasts but no measured soil data tend to be over- or underestimated. A well-distributed sampling network, extended even to high elevation regions, increased the mapping accuracy compared to an extrapolated approach without measured soil samples within the predicted area. Our results suggest that the soil erodibility in other Alpine countries might also be under-/ overestimated due to a lack of topsoil samples on mountainous regions. A sampling of mountainous regions as was done in this study in Switzerland should be envisaged in future campaigns of Alpine countries to reduce that uncertainty in soil erodibility and in soil loss assessments.

By modeling the K-factor of Switzerland we were able to fill the Swiss blank spot in the European soil erodibility map and

make the Swiss values comparable to other European countries. However, caused by the number of samples and spatial resolution, the map should be used as an overview, indicating trends and regional differences within Switzerland or to neighboring countries and not as a detailed map for local studies. The mapping approach could be further improved by additional topsoil data and spatial high resolution covariates (e.g., NABODAT, Rehbein et al., 2017; SwissAlti3D, Swisstopo, 2018a). Unfortunately, most of the existing Swiss topsoil datasets do not have a national coverage and a harmonization of several datasets is impeded by various data owners, different sampling campaigns and applied sampling and analytical methodologies. It would be conceivable to use these clustered data (e.g., NABODAT data, Rehbein et al., 2017) in addition to high resolution predictors to model soil erodibility for specific regions of Switzerland with a high sampling density (e.g., for Swiss midland). The calculation of the soil erodibility for the blank spot of Switzerland on the map has not only an added value for European soil erosion risk assessments, but delivers further valuable information on a continental scale for other environmental and soil related issues like site-specific land use decisions, soil and land suitability, and soil protection including agro-economic considerations.

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