Integrated Biodiversity Management, South Caucasus

Erosion risk assessment: Comparison of remote sensing and field sampling in the pilot area Tusheti, Georgia

Hanns Kirchmeir & Vanessa Berger (E.C.O.)

Report

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Author of this report

Hanns Kirchmeir & Vanessa Berger (E.C.O. Institute of Ecology)

Photographs

Hanns Kirchmeir

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List of Abbreviations

BMZ	German Federal Ministry of Economic Cooperation and Development
GIZ	Deutsche Gesellschaft fuer Internationale Zusammenarbeit GmbH
GPS	Global Positioning System
IBiS	Integrated Biodiversity Management, South Caucasus [Project]
NGO	Non-governmental Organization
RUSLE	Revised Universal Soil Loss Equation
SEI	Susceptibility to Erosion-Index
TPA	Tusheti Protected Areas

1. Introduction

The key challenge in high mountain areas of the South Caucasus is the unsustainable use of pastures and forest areas that leads to erosion, degradation, desertification and loss of biodiversity. The programme “Integrated Biodiversity Management in the South Caucasus” (IBiS)” contributes to rehabilitation of degraded areas and conservation of biodiversity through the protection of natural resources from anthropogenic induced erosion processes.

To assess the current state and general risk of erosion, a remote sensing tool – the Erosion Sensitivity Model - was developed by the Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) GmbH in cooperation with national experts in Armenia. The technology was also transferred to Georgia and Azerbaijan. Experts from Armenia and Georgia were working on remote sensing tools to estimate the risk of erosion.

For the Georgian Pilot Region Tusheti Protected Areas (TPA) the remote sensing approach was implemented by GIS-LAB- In Georgia the **Revised Universal Soil Loss Equation** (**RUSLE,** Renard et al. 1996) was adopted to the Caucasian environment by the expert team of GIS-LAB (Mikeladze & Nikolaeva 2016, Mikeladze & Megvinetukhutsesi 2018, Kirchmeir 2017).

Another approach was chosen by Jonathan Etzold (2013) with his pasture assessment tool developed in Azerbaijan and implemented now in several projects in all three countries of the South Caucasus. His aim was to give shepherds a simple field-toolkit to estimate the susceptibility to erosion and the state of pasture quality.

Both approaches are rating topsoil erosion having rainfall and surface water runoff as the main driver of erosion and the vegetation cover, soil parameters and the geomorphological situation as relevant co-variables.

Both approaches have been applied in Tusheti Protected Landscapes in Georgia and this paper deals with a statistical comparison of the results.

2. Methodology

2.1 Data

2.1.1 Remote sensing

The remote sensing approach for the "Erosion Sensitivity Model" as developed by GIZ in Armenia was applied to the pilot area of Gometsari Gorge in Tusheti Protected Areas (Georgia). This model is a further development of the Universal Soil Loss Equation (USLE, Wischmeier and Smith 1965, 1978) and its further development, the Revised Universal Soil Loss Equation (RUSLE, Renard et al. 1996).

The "Erosion Sensitivity Model" estimates soil loss in tons per acre based on input factors such as precipitation, soil type, slope and vegetation cover. As data source for the precipitation the "CHELSA – Climatologies at high resolution for the earth's land surface areas" data platform was used (Karga et al. 2017). On the basis of the soil map (resolution 1:200,000) the soil erodibility factor which represents the susceptibility of soil to erosion and the rate of runoff was estimated. The relief characteristics such as the inclination and the slope length were taken from an elevation model derived from the Soviet topographic maps. Sentinel 2 images (European Space Agency – ESA) were used to estimate vegetation cover by comparing the ratio between the visible red light and invisible near infrared (estimation of chlorophyll amount). Based on this comparison the data was classified with the Support Vector Machine technology and the Jeffries-Matusita, Transformed Divergence algorithm (Mikeladze & Nikolaeva 2016). The spectral signature of the Sentinel images was also used to estimate Biomass data. For this purpose, biomass samples were collected in Tusheti and then extrapolated (Kirchmeir, 2017).

2.1.2 Field samples

The field data was collected during the years 2016, 2017 and 2018 within the vegetation monitoring and pasture assessment using the Monitoring Manual from Etzold et al. (2013) by an expert team from NACRES (see Table 1).

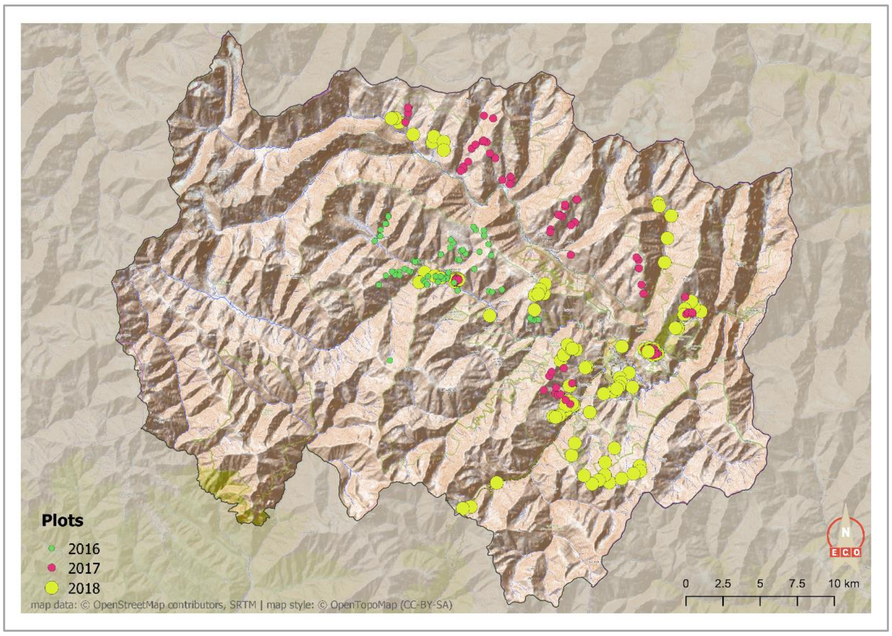


Figure 1: Location of collected plots for each survey year

The pasture quality approach from Etzold (2013) was developed for quick and easy assessment of a pasture unit in the field. General site description and vegetation characteristics were estimated, and the coordinates of each monitoring plot were located using handheld GPS (Garmin 64). The plot size was 10x10m. At each plot the ground coverage, bare soil, stones, signs for erosion and livestock tracks are assessed in given classes. The percentage of Erosion tracks is a combination of bare soil, bare stones and visible erosion processes. Furthermore, various indices were calculated based on these collected field data. Among other the Susceptibility to Erosion-Index (SEI) is composed of physical parameters to assess the potential of erosion at each plot. The calculation of Susceptibility to Erosion-Index (Etzold et al., 2013) is based on variables which are assessed in the field (altitude, inclination, aspect, topographic position, slope configuration and bedrock). Each indicator value is transformed into an index value (nominal, ordinal and metric levels of measurement) rating from 0 (high contribution to erosion risk) to 20 (no contribution to erosion risk). The result ranges from 0 until 100. **This inverse rating schema leads to high SEI values, when the erosion risk is low and low SEI values, when the erosion risk is high. This needs to be taken into consideration when interpreting the results of the analysis.** Additional to the indicators defined by Etzold 2013 the percentage of vegetation cover was assessed as well.

Table 1: Amount of monitoring plots assessed in the Geobotanical survey and the Vegetation Monitoring.

Vegetation Monitoring	
June/July 2017	46
Geobotanic survey	
2016	65
2017	58
Pasture Evaluation Plots	
2018	79
Total	**248**

2.1.3 Data comparison

For further computation the RUSLE data (Mikeladze et al., 2016) were compared with the pasture quality approach from Etzold (2013) as ground truthing.

To compare the results from field samples and remote sensing data the coordinates of the field samples where used as a link. As the GPS (Garmin 64) delivers data with an uncertainty of the real position in average of 5-20m, the original plot coordinates where buffered by a radius of 10m (20m, 30m and 40m) to compensate the uncertainty of the position assessed by GPS in the field. Within the radius a mean value of the RUSLE results of the remote sensing approach was calculated. The RUSLE raster data has a resolution of 10x10m for whole Tusheti so 4-9 values are within the 10m radius (Figure 2).

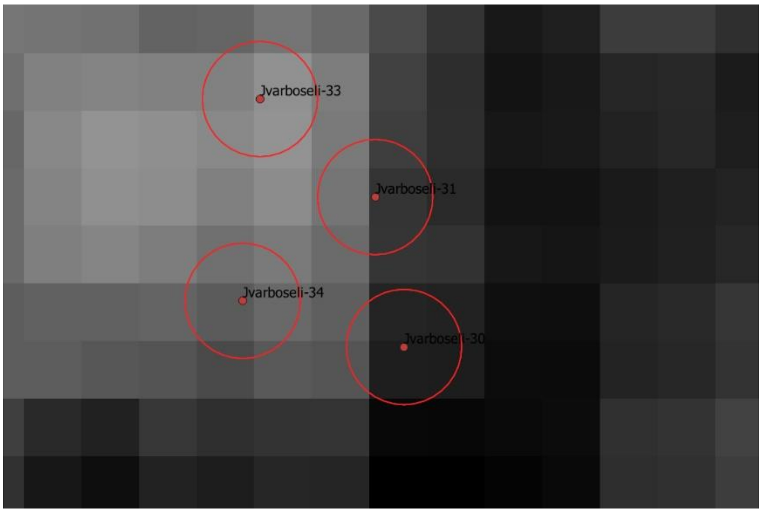


Figure 2: As shown in this figure for each field plot (red dot) the raster data (with a pixel resolution of 10x10m) was averaged in an 10m radius(red circle).

The Erosion Tracks were estimated in percentage for currently recognizable erosion processes within the plot. To compare RUSLE results (metric) with the Erosion Tracks it is important to take into account that the uneven distribution of classes leads to a reduction in the comparability of estimates between different operators. However, a comparable data basis is decisive for the large-scale application of the Monitoring Manual for Winter Pastures in the Transcaucasus (Etzold et al., 2013), which is difficult with a logarithmic distribution. 1% in the personal assessment can cause the mean difference of the classes from for instance 3 up to 37 % (Figure 3).To use the actual erosion (e.g. erosion tracks) as ground truthing for remote sensing data there is a need of regular distributed classes in field assessment.

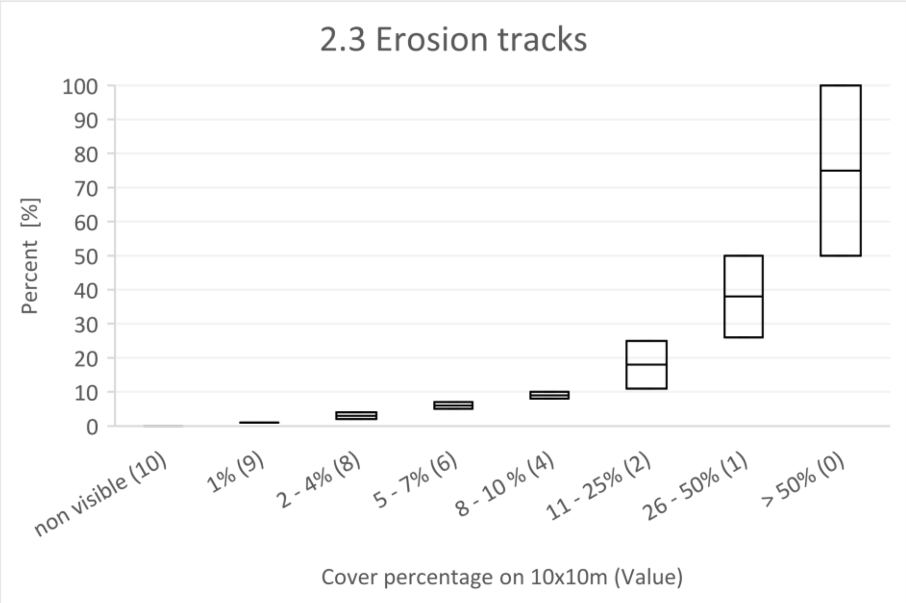


Figure 3: Representation of the different class sizes shown on the example of Erosion Tracks. The parenthesis indicates the value for further calculation of the indices.

For further statistical analysis the data was imported and tested in "R", a software for statistical analysis (version 3.6.1.).

To compare the variability between the SEI and the different buffer distances a linear regression was calculated with a logarithmic transformation.

Further statistic relationships were tested for SEI and RUSLE as well as for Erosion Tracks and for RUSLE and Erosion Tracks. For this statistical test, the Spearman rank correlation coefficient was calculated because of the comparison of non-parametric continuous and ordinal variables. The Spearman coefficient examine monotonic relationships (even not linear). A perfect result for a negative correlation of two values is -1 which means for instance an increase in Erosion Tracks leads always to a decrease in SEI while 0 indicates no correlation between the two variables.

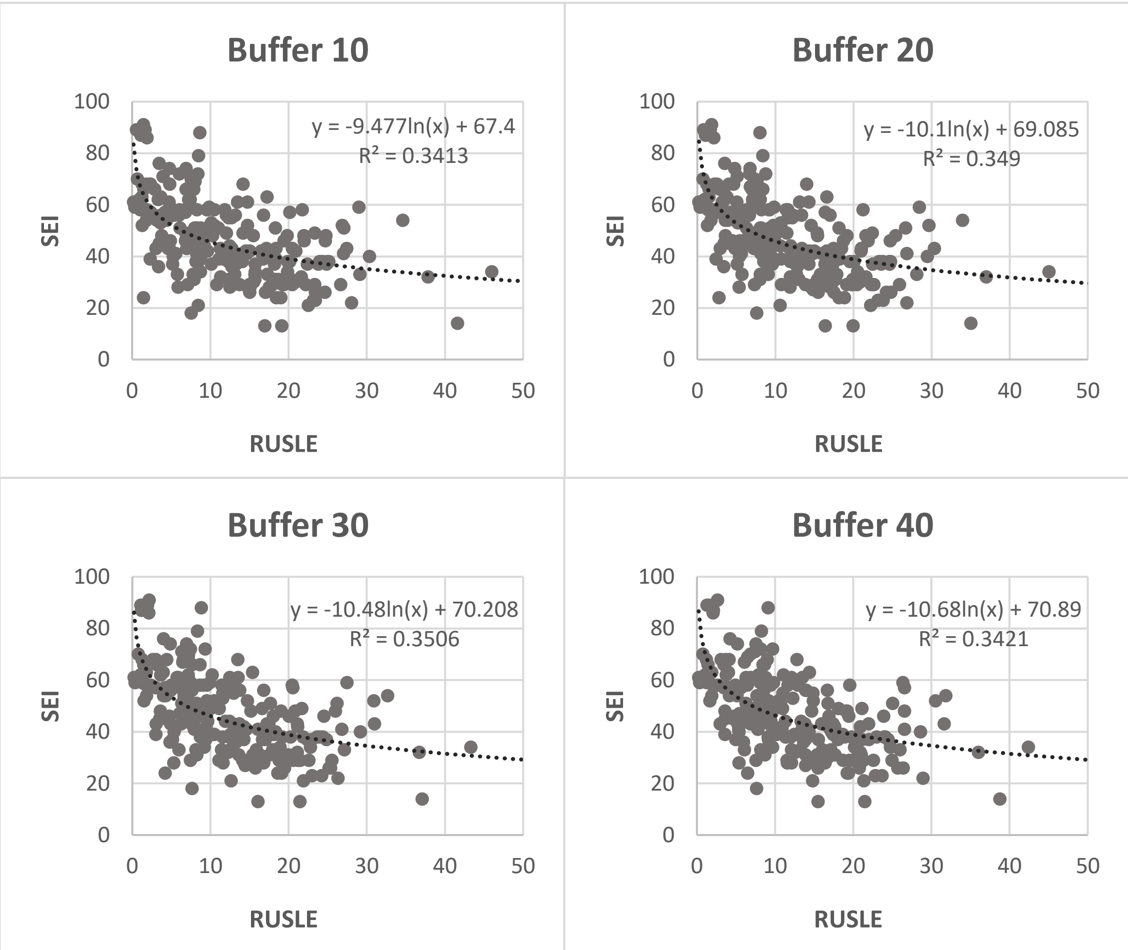
For this test, each plot is only used once for the analysis (n=248). The vegetation monitoring data was therefore only used for July 2017.

3. Results

The average RUSLE value was calculated in a radius of 10, 20, 30 and 40m from the field location point to evaluate the correlation between the Susceptibility to Erosion-Index (based on field data) and the RUSLE results (based on remote sensing). The analysis showed a logarithmic correlation of SEI and the RUSLE results (**Error! Reference source not found.**). The coefficient of determination was slightly increasing from 0.341 at 10m buffer up to 0.350 for a 30m buffer radius. A further expansion up to a buffer of 40m leads to a slight decrease in the coefficient of determination.

The results indicated a decline in variation with growing buffer distance. This might be explained by the error in the position of the field data as well as in human bias between field experts in the assessment of value. Some error might also be caused by the coarse input data for RUSLE calculation in the remote sensing approach. Based on this result, the 30m radius was used for further calculations.

Nevertheless, the analysis shows a high correlation of the remote sensing data with the field data.



Comparison of the Correlation between SEI and RUSLE (n =248) with different buffer approaches.

To understand better the variability and reliability of the data, we compared the SEI with a second indicator directly assessed in the field, the Erosion Tracks value. The Erosion Tracks have not been used to calculate the SEI and can be used to evaluate the strength of the SEI to explain the current situation of erosion. The Susceptibility to Erosion-Index (SEI) does not necessarily describe the current impact of erosion, but it can be assumed, that sites of a low SEI (remember the inverse rating system!) are more likely to show a higher percentage of Erosion Tracks than sites with high SEI. **Error! Reference source not found.** is showing the variability of the SEI values within each Erosion Track assessment classes. A clear trend is visible between the two variables, but still there is high variability of SEI within the same class of the Erosion track assessment.

Both, SEI and RUSLE are values to describe the erosion risk of a site. The Erosion Tracks assessed in the field can be used to evaluate the predictive accuracy of this two erosion risk index values.

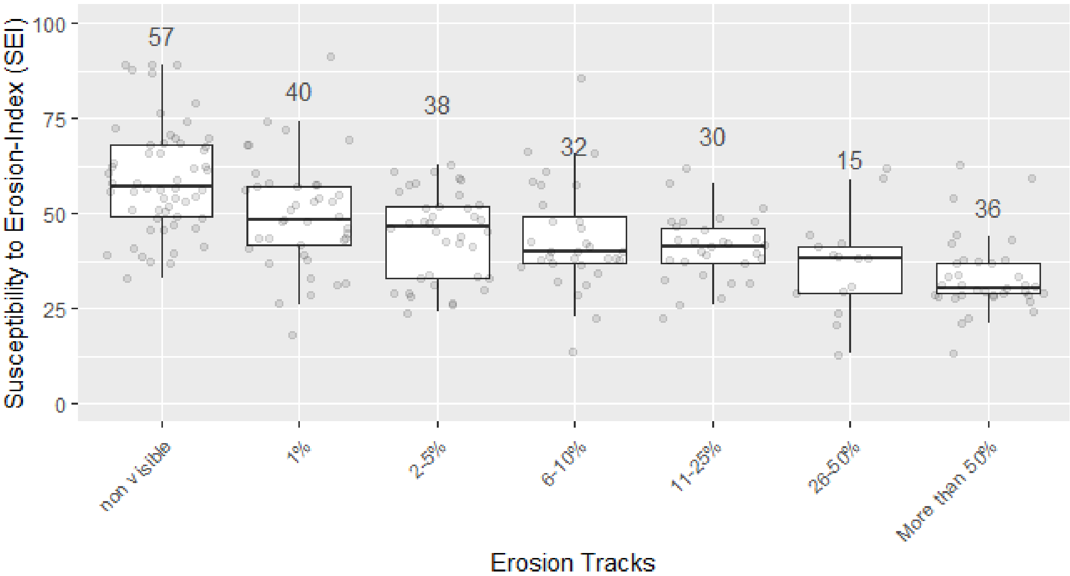


Figure 4: Distribution of Susceptibility to Erosion-Index (SEI) on assessed Erosion Track classes. The grey points symbolize the SEI distribution within the Erosion Track classes and the number represent the number of plots in each boxplot.

The Spearmann coefficient for the comparison of SEI and Erosion track was -0.57 ($p < .001$).

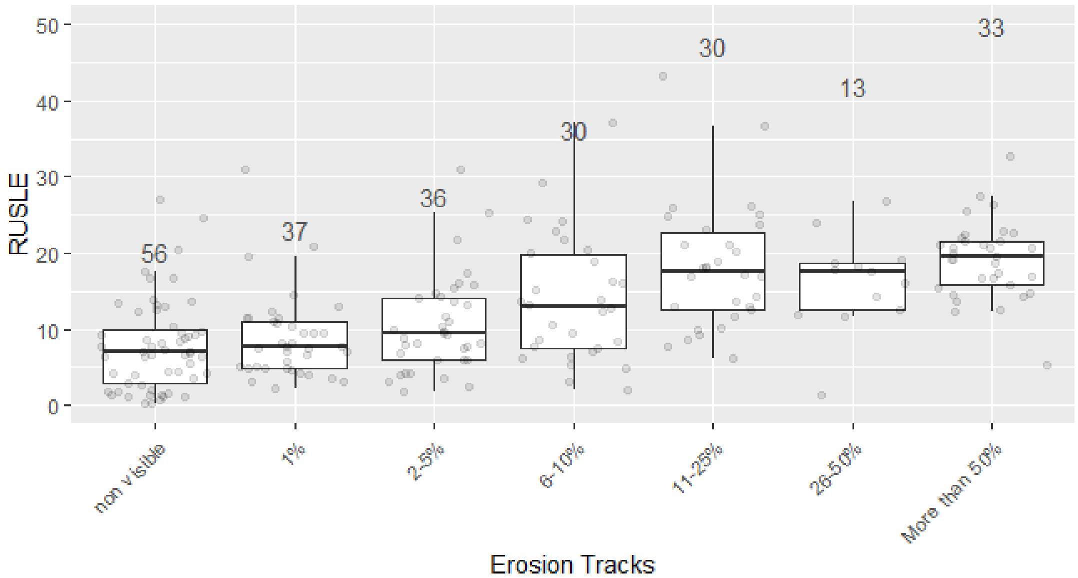


Figure 5: Distribution of RUSLE on assessed Erosion Track classes. The grey points symbolize the SEI distribution within the Erosion Track classes and the number represent the number of plots in each boxplot.

The comparison of RUSLE with the Erosion Tacks shows an increasing RUSLE value with increasing Erosion Tracks (Figure 5) and a statistically significant Spearmann correlation of 0.57 ($p < .001$). This positive relationship indicates the suitability of the Erosion tracks field assessment for ground truthing.

The Spearman coefficient describing the relation between SEI and Erosion Tracks is -0.57 ($p < .001$) and exactly the same as the Spearman coefficient describing the relation between RUSLE and the Erosion Tracks. This means, that both erosion risk assessment approaches, SEI based on field assessment and RUSLE based on remote sensing, show the same strength and confidence in prediction of the Erosion Tracks assessed in the field.

A comparison on the SEI and the RUSLE shows a Spearman coefficient of -0.59 ($p < .001$) at a radius of 30m. The results for the different radii also show an increasing relationship with growing radius until 30m.

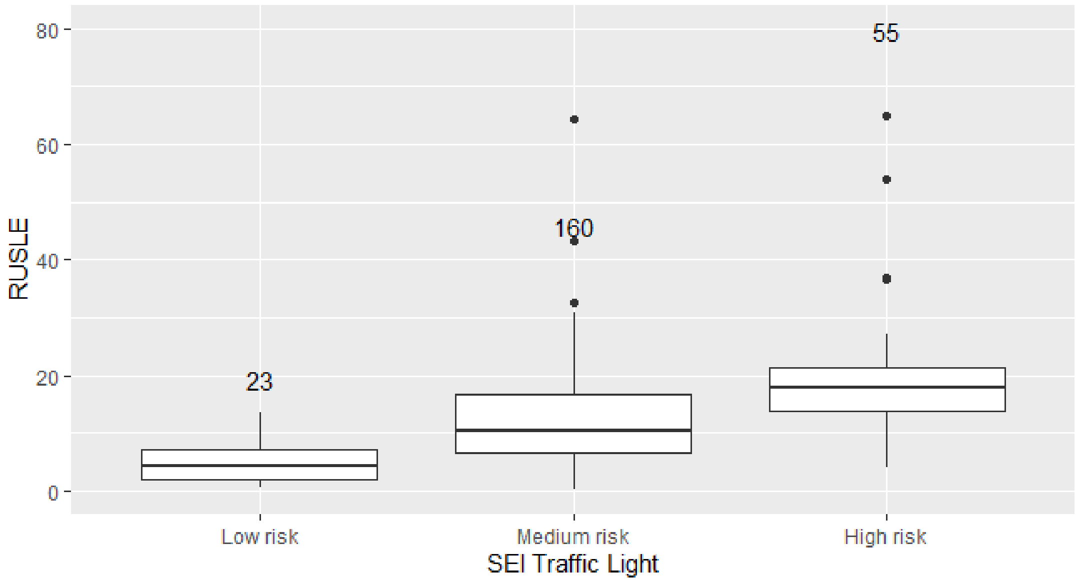


Figure 6: Grouped RUSLE results in Susceptibility to Erosion-Index classified (n=248) in Low risk (median RUSLE was 4.38), Medium risk (median RUSLE was 10.34) and High risk (median RUSLE was 17.92).

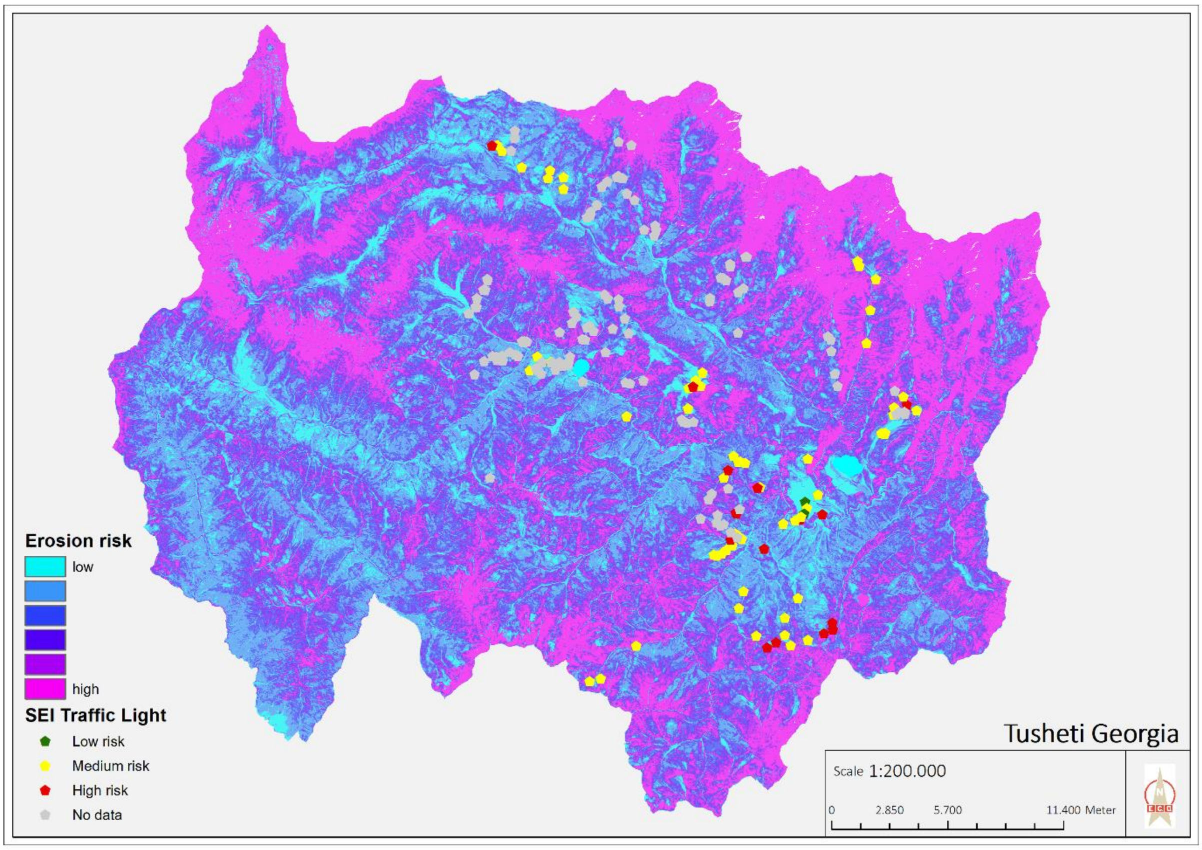


Figure 7: Erosion risk map with field data location classified by the Traffic Light of the Susceptibility to Erosion-Index.

Grouping RUSLE into the Traffic Light classes of the SEI values showed that most plots are at medium risk (160). The median of RUSLE for high risk SEI was 17.92 and 10.34 for medium risk. The comparison of these results with the total RUSLE values for grassland of Tusheti Protected Areas (Figure 8) showed that large areas have a medium susceptibility to erosion and most grassland areas a high susceptibility to erosion.

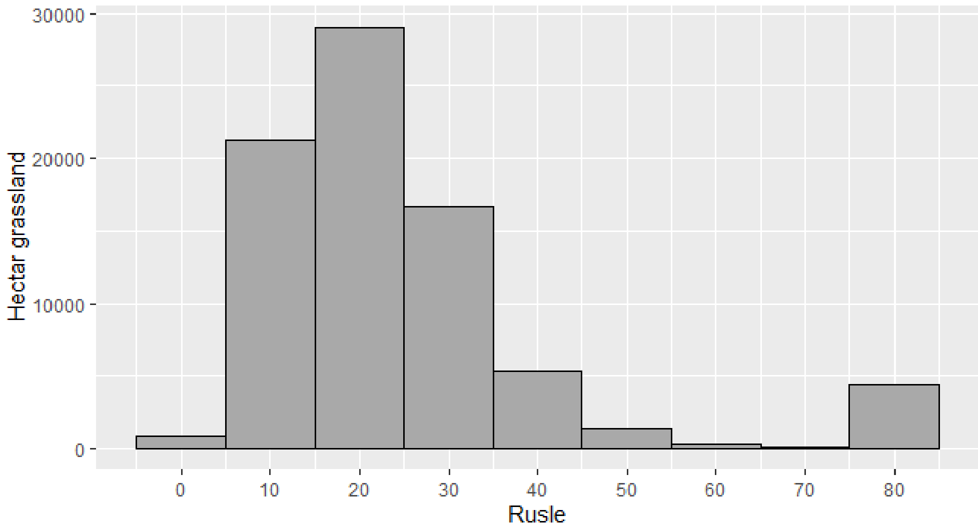


Figure 8: Distribution of RUSLE values per hectare grassland in Tusheti Protected Areas.

4. Conclusion

The Spearman coefficient describing the relation between SEI and Erosion Tracks is -0.57 ($p < .001$) and in a very similar range than the Spearman coefficient describing the relation between RUSLE and Erosion Tracks (0.57, $p < .001$).

A comparison on the SEI and the RUSLE shows a Spearman coefficient of -0.59 at a radius of 30 m for mean RUSLE value of each field plot. This indicates, that even between the field data (SEI compared to Erosion Tracks) the monotonic relationship is less consistent than for SEI and the RUSLE value based on remote sensing data.

The advantage of the SEI based on Etzold 2013 is an easy to use and robust field method. The SEI is without dimension, but can help to rate low, medium and high erosion risk on a specific site. Beside the erosion assessment, many other variables (e.g. number of plant species, amount of pasture weeds) can be assessed in the field, which is impossible to assess from remote sensing data.

The disadvantage of the SEI method is its limited capability to describe large pasture units, as it is just accurate for the sample plot and cannot be precisely extrapolated.

The advantage of the RUSLE value based on implementation by Mikeladze & Nikolaeva 2016 is the huge area that can be covered, and the approach can be easily repeated to monitor changes. The RUSLE value is a metric variable and is describing the tons of soil washed out by erosion each year. Additional attributes like land cover classification and grassland biomass can be derived with the same remote sensing data.

The disadvantage of the RUSLE approach is, that you need highly skilled GIS professionals to apply the method.

The combination of field samples with remote sensing data has the great potential, to deliver valuable data on land cover, biomass distribution and erosion risk on large territories. Once calibrated by field data, the remote sensing approach can be repeated based on the same sensor data (e.g. Sentinel 2) to calculate precisely changes in erosion risk or land cover.

5. Reference:

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6. Appendices

Table 1: Data-Input for Statistical analysis of SEI and RUSLE (source as above explained: Geobotanic survey (2017), Vegetation Monitoring, RUSLE results, Biomass)

Year	Plot number	1.1.3 Elevation	1.2.1 Inclination [°]	1.2.2 Aspect [°]	2.3. Erosion Track	3.2.2 Total vegetation cover	SEI	SEI-Traffic	RUSLE buffer 10m	RUSLE buffer 20m	RUSLE buffer 30m	RUSLE buffer 40m	Biomass buffer 20m
2016	A001	1896	32	0	6-10%	0.91	61	Medium risk	7.4	7.1	7.1	6.8	190.2
2016	A002	1889	10	90	1%	0.97	91	Low risk	1.4	1.9	2.1	2.6	257.9
2016	A003	1901	18	90	non visible	0.99	76	Low risk	3.5	3.5	4.0	4.2	341.3
2016	A004	2044	35	180	11-25%	0.7	46	Medium risk	19.4	18.7	18.0	16.9	129.5
2016	A005	1935	29	225	non visible	0.99	61	Medium risk	13.5	13.1	12.5	12.1	247.2
2016	A006	1821	27	0	1%	0.82	69	Low risk	8.1	7.7	7.1	6.5	214.2
2016	A007	2001	32	90	2-5%	0.94	51	Medium risk	8.0	8.1	8.2	8.3	241.7
2016	A008	2326	35	225	11-25%	0.66	43	Medium risk	11.3	11.9	12.9	13.6	106.0
2016	A009	2567	12	225	non visible	1	63	Medium risk	1.3	1.5	1.8	1.9	484.1
2016	A010	2563	16	45	non visible	1	68	Low risk	2.2	2.2	2.6	3.1	441.6
2016	A011	2920	28	225	6-10%	0.88	52	Medium risk	10.0	9.8	9.5	9.2	131.4
2016	A012	3031	21	180	2-5%	0.9	44	Medium risk	9.2	9.6	9.6	9.5	130.5
2016	A013	3015	15	270	6-10%	0.85	57	Medium risk	6.8	6.5	6.2	5.6	115.3
2016	A014	2802	37	315	1%	0.97	49	Medium risk	NA	NA	NA	NA	NA
2016	A015	2743	35	270	non visible	0.93	46	Medium risk	24.7	24.7	24.5	23.9	183.6
2016	A016	1944	30	180	non visible	1	51	Medium risk	8.2	8.2	8.2	8.0	433.7
2016	A017	2128	23	180	2-5%	0.85	61	Medium risk	14.8	14.3	13.5	13.5	149.5
2016	A018	2082	39	180	11-25%	0.7	51	Medium risk	27.1	26.7	26.2	25.0	117.7
2016	A019	2085	10	0	non visible	0.99	89	Low risk	1.5	1.4	1.4	1.5	301.4
2016	A020	2168	37	180	11-25%	0.55	46	Medium risk	4.9	5.5	7.7	9.2	128.3
2016	A021	2196	11	0	non visible	0.99	89	Low risk	1.7	1.7	1.9	1.9	305.1
2016	A022	2344	37	135	non visible	1	51	Medium risk	18.3	18.1	17.7	16.8	401.1
2016	A023	2230	39	135	More than 50%	0.35	59	Medium risk	29.0	28.5	27.4	26.3	97.9

2016	A024	2196	34	135	More than 50%	0.45	54	Medium risk	34.6	34.0	32.6	31.8	95.3
2016	A025	2079	5	180	non visible	0.93	87	Low risk	1.1	1.1	1.2	2.1	192.2
2016	A026	2328	34	315	non visible	0.98	49	Medium risk	14.2	15.4	16.6	18.1	154.0
2016	A027	2633	34	270	2-5%	0.97	52	Medium risk	14.8	14.6	14.7	14.9	242.0
2016	A028	2717	20	135	non visible	0.98	70	Low risk	7.6	7.4	7.2	6.9	241.7
2016	A029	2241	19	315	non visible	0.97	71	Low risk	4.0	5.1	6.3	7.4	144.6
2016	A030	2279	27	225	6-10%	0.84	58	Medium risk	21.8	21.2	20.4	19.6	116.0
2016	A031	2340	35	180	11-25%	0.67	48	Medium risk	24.8	25.4	26.0	26.6	91.5
2016	A032	2168	25	135	1%	0.97	58	Medium risk	9.6	9.2	9.5	9.4	302.1
2016	A033	2185	12	0	6-10%	0.99	86	Low risk	1.9	2.1	2.1	2.0	269.5
2016	A034	2223	18	45	non visible	1	79	Low risk	8.5	8.4	8.3	8.2	209.9
2016	A035	2425	17	0	non visible	1	72	Low risk	8.4	8.8	9.3	9.7	189.4
2016	A036	2523	11	90	1%	0.96	74	Low risk	4.8	4.8	4.9	5.2	176.8
2016	A037	2473	36	180	11-25%	0.88	48	Medium risk	8.6	8.9	9.2	9.0	130.8
2016	A038	2418	24	135	2-5%	0.95	55	Medium risk	12.7	12.2	11.6	11.0	126.7
2016	A039	2307	23	135	2-5%	0.93	56	Medium risk	12.1	12.3	13.2	13.9	204.5
2016	A040	2288	10	180	1%	0.95	72	Low risk	6.0	6.7	7.4	8.2	175.1
2016	B001	2310	32	180	2-5%	0.98	48	Medium risk	10.3	9.9	9.5	9.1	208.9
2016	B002	2550	30	180	1%	0.9	48	Medium risk	NA	NA	NA	NA	NA
2016	B003	2629	16	225	non visible	0.99	68	Low risk	4.8	4.7	4.4	4.1	347.1
2016	B004	2915	0	-1	non visible	0.8	88	Low risk	8.7	8.1	8.8	9.1	134.8
2016	B005	3080	10	225	2-5%	0.6	61	Medium risk	0.7	3.2	5.9	8.8	102.5
2016	B006	2910	22	90	1%	0.98	58	Medium risk	11.9	11.6	11.4	11.6	125.2
2016	B007	2513	40	180	More than 50%	0.4	34	Medium risk	19.9	20.5	22.8	24.7	101.2
2016	B008	2115	10	135	non visible	0.98	74	Low risk	6.9	6.8	6.9	7.5	377.8
2016	B009	2091	40	225	11-25%	0.65	43	Medium risk	20.5	21.0	21.1	22.0	112.3
2016	B010	2195	15	135	1%	0.98	68	Low risk	2.4	2.5	3.0	3.7	195.0
2016	B011	2222	27	270	2-5%	0.97	58	Medium risk	1.0	1.4	1.8	2.0	263.7
2016	B012	2263	26	0	non visible	0.99	67	Medium risk	7.4	6.8	6.4	6.1	288.2

2016	B013	2255	30	135	non visible	0.99	57	Medium risk	20.2	16.4	20.5	26.5	206.9
2016	B014	2223	34	90	11-25%	0.7	62	Medium risk	7.4	8.1	10.2	11.1	123.8
2016	B015	2119	40	270	6-10%	0.85	46	Medium risk	22.0	21.9	20.0	19.4	160.8
2016	B016	2080	4	135	non visible	0.97	89	Low risk	0.6	0.8	1.1	1.3	246.3
2016	B017	2320	16	180	26-50%	0.4	62	Medium risk	NA	NA	NA	NA	NA
2016	B018	2612	29	180	2-5%	0.8	52	Medium risk	26.9	29.7	30.9	30.5	NA
2016	B019	2809	23	90	1%	0.98	58	Medium risk	5.3	5.1	5.0	4.9	232.6
2016	C001	2533	18	315	non visible	1	68	Low risk	14.2	14.0	13.5	12.8	166.9
2016	C002	2538	25	315	non visible	1	58	Medium risk	10.5	11.4	12.3	12.9	111.7
2016	C003	2588	26	135	1%	0.95	55	Medium risk	12.4	11.6	12.9	14.9	151.7
2016	C004	2659	28	135	2-5%	0.85	49	Medium risk	12.1	11.5	11.1	11.0	166.7
2016	C005	2321	33	180	11-25%	0.4	48	Medium risk	19.8	19.2	19.0	19.1	86.8
2016	C006	2406	20	315	1%	0.98	68	Low risk	1.8	4.1	6.5	9.0	143.6
2017	cza01	2064	20	NA	1%	0.95	48	Medium risk	8.4	8.3	8.2	8.2	177.0
2017	cza02	2231	16	180	non visible	0.88	54	Medium risk	3.2	3.6	4.3	5.1	379.4
2017	Cza03	2234	12	135	1%	0.95	57	Medium risk	4.2	4.0	4.2	4.3	346.4
2017	Cza04	2624	33	45	1%	0.95	26	High risk	17.0	17.5	19.5	20.8	98.2
2017	Cza05	2626	NA	NA	2-5%	0.9	26	High risk	15.1	15.5	15.7	15.5	182.1
2017	Cza06	2302	21	135	non visible	0.95	39	Medium risk	2.3	2.4	3.0	3.6	674.6
2017	Cza07	1957	15	135	1%	0.95	51	Medium risk	11.0	10.8	10.8	10.7	139.6
2017	Cza08	2565	25	225	1%	0.95	33	High risk	7.8	9.1	11.4	13.2	169.6
2017	Cza09	2584	28	315	6-10%	0.9	38	Medium risk	14.1	13.3	12.4	11.3	121.6
2017	Cza10	2407	11	135	non visible	0.95	58	Medium risk	9.7	9.3	9.0	8.9	339.0
2017	Cza11	2327	22	45	non visible	0	33	High risk	29.2	28.1	27.1	26.0	132.2
2017	Cza12	2135	28	180	11-25%	0.45	32	High risk	21.7	21.6	21.1	20.9	94.9
2017	Cza13	2235	10	135	1%	0.9	61	Medium risk	4.7	5.1	5.7	6.3	157.9
2017	Cza14	2227	36	180	11-25%	0.5	34	Medium risk	46.0	45.1	43.3	42.4	90.7
2017	Cza15	2173	NA	NA	2-5%	0.95	29	High risk	13.8	13.9	14.1	14.7	115.8
2017	Cza16	2212	12	NA	2-5%	0.85	49	Medium risk	23.4	22.4	21.7	21.1	104.7

2017	Cza17	2760	18	180	non visible	1	39	Medium risk	8.8	9.8	10.4	11.1	270.9
2017	cza18	3018	31	225	More than 50%	0.4	13	High risk	19.2	20.0	21.4	21.5	82.2
2017	Cza19	2092	29	180	11-25%	0.76	38	Medium risk	19.9	20.1	20.2	20.4	99.0
2017	Cza20	2270	17	225	1%	0.95	52	Medium risk	10.5	10.3	10.4	10.5	167.6
2017	Cza21	2278	23	315	1%	0.95	42	Medium risk	9.6	9.3	9.4	9.6	166.4
2017	Cza22	2207	18	180	1%	0.97	53	Medium risk	10.2	10.7	11.5	12.3	120.2
2017	Cza23	2281	42	225	26-50%	0.65	13	High risk	17.0	16.4	16.0	15.5	107.6
2017	Cza24	2985	28	225	2-5%	0.6	30	High risk	15.5	15.8	16.1	16.4	99.8
2017	Cza25	2901	28	270	2-5%	0.65	33	High risk	57.2	55.0	64.8	69.1	NA
2017	Cza26	2941	22	225	2-5%	0.5	31	High risk	15.7	15.4	15.4	15.4	88.8
2017	Cza27	2836	23	135	2-5%	1	33	High risk	8.1	8.1	8.1	8.2	269.8
2017	Cza28	2508	26	135	2-5%	0.85	33	High risk	5.8	5.8	6.0	6.1	315.4
2017	Cza29	2653	30	135	2-5%	0.9	29	High risk	NA	NA	NA	NA	NA
2017	Cza30	2369	NA	180	non visible	0.95	47	Medium risk	8.6	8.7	9.2	9.5	141.8
2017	Cza31	2369	20	180	non visible	0.95	56	Medium risk	16.8	17.0	16.8	16.7	142.2
2017	Cza32	2714	26	270	non visible	0.95	56	Medium risk	13.2	13.4	13.7	14.0	181.9
2017	Cza33	3001	26	135	1%	0.9	41	Medium risk	14.7	14.8	14.6	14.2	121.5
2017	Cza34	3119	33	180	6-10%	0.2	23	High risk	23.5	23.8	24.2	23.7	82.5
2017	Cza35	3121	32	135	11-25%	0.26	26	High risk	23.5	24.2	25.1	26.4	83.3
2017	Cza36	2681	NA	NA	6-10%	0.95	32	High risk	NA	NA	NA	NA	NA
2017	Cza37	2345	16	135	non visible	1	54	Medium risk	4.4	5.8	6.6	7.7	298.0
2017	Cza38	2520	12	225	non visible	1	41	Medium risk	5.6	5.7	5.4	5.3	377.5
2017	Cza39	2784	24	225	1%	1	31	High risk	7.9	8.0	8.2	8.7	187.9
2017	Cza40	2944	6	225	2-5%	1	42	Medium risk	16.5	16.6	17.3	17.6	116.9
2017	Cza41	2967	4	225	2-5%	0.65	46	Medium risk	7.5	8.3	8.7	9.2	113.0
2017	Cza42	2120	33	225	More than 50%	0.25	24	High risk	18.4	18.2	18.6	19.2	82.7
2017	Cza43	2143	16	180	1%	0.97	54	Medium risk	3.7	3.9	4.0	4.1	260.3
2017	Cza44	2442	20	270	2-5%	0.88	48	Medium risk	7.1	6.9	6.9	6.8	261.9
2017	Cza45	2605	20	180	2-5%	0.97	45	Medium risk	4.1	4.1	4.3	4.6	291.9

2017	Cza46	2753	8	225	1%	0.99	45	Medium risk	3.5	3.4	3.5	3.6	367.8
2017	Cza47	2864	NA	270	1%	0.92	29	High risk	10.8	10.8	11.1	11.5	115.4
2017	Cza48	3018	31	225	26-50%	0.4	24	High risk	19.0	18.9	19.1	19.4	84.1
2017	Cza49	2601	13	180	non visible	0.99	54	Medium risk	1.9	1.8	1.8	1.9	752.5
2017	Cza50	2426	14	270	6-10%	0	66	Medium risk	2.9	2.9	3.1	3.5	325.6
2017	Cza51	2789	18	135	2-5%	0.95	59	Medium risk	7.2	7.2	7.5	8.1	363.7
2017	Cza52	2952	21	135	26-50%	0.75	44	Medium risk	12.5	12.0	11.9	11.3	156.3
2017	Cza53	2515	39	180	1%	0.85	32	High risk	11.3	11.9	12.3	12.6	335.0
2017	Cza54	NA	38	180	6-10%	0.95	48	Medium risk	15.5	15.4	15.2	14.7	306.6
2017	Cza55	2482	26	315	non visible	0.95	53	Medium risk	NA	NA	NA	NA	NA
2017	Cza56	2319	27	180	6-10%	0.8	29	High risk	7.1	7.3	7.4	7.6	184.6
2017	Cza57	2386	21	135	1%	0.9	39	Medium risk	NA	NA	NA	NA	NA
2017	Cza58	2653	30	135	2-5%	0.9	34	Medium risk	8.7	8.9	9.2	9.7	189.5
2017	Jvarboseli-30	1977	28	182	1%	NA	38	Medium risk	8.2	9.3	9.5	9.3	216.1
2017	Jvarboseli-31	1987	32	189	More than 50%	NA	37	Medium risk	13.3	14.3	14.3	13.9	164.1
2017	Jvarboseli-33	1991	33	152	6-10%	NA	31	High risk	18.7	17.4	16.3	15.9	140.6
2017	Jvarboseli-34	1974	30	203	2-5%	NA	28	High risk	15.1	14.6	14.3	12.1	198.4
2017	Jvarboseli-41	2083	25	198	11-25%	NA	39	Medium risk	13.4	13.2	13.0	13.0	156.1
2017	Jvarboseli-42	2129	36	185	More than 50%	NA	31	High risk	12.3	13.0	13.6	13.9	130.2
2017	Jvarboseli-43	2066	21	189	non visible	NA	37	Medium risk	12.7	12.6	13.1	13.6	188.0
2017	Jvarboseli-44	2120	39	191	More than 50%	NA	28	High risk	17.6	17.0	16.8	16.4	126.2
2017	Jvarboseli-45	2066	31	164	More than 50%	NA	27	High risk	15.0	14.8	14.4	13.9	156.3
2017	Jvarboseli-46	2115	29	190	More than 50%	NA	37	Medium risk	18.2	17.4	16.6	15.5	117.2
2017	Jvarboseli-47	2048	26	185	6-10%	NA	38	Medium risk	12.9	13.1	12.6	12.0	201.0
2017	Jvarboseli-48	2090	24	205	11-25%	NA	39	Medium risk	13.0	13.1	12.5	12.5	153.2
2017	Shenako-11	2032	27	188	26-50%	NA	38	Medium risk	25.2	24.6	24.0	23.0	116.9
2017	Shenako-12	2031	27	185	6-10%	NA	38	Medium risk	24.9	24.8	24.4	24.1	115.4
2017	Shenako-13	2032	26	198	11-25%	NA	37	Medium risk	24.9	24.6	24.8	24.4	114.1
2017	Shenako-14	2026	24	200	6-10%	NA	37	Medium risk	23.8	23.6	22.9	21.1	134.7

2017	Shenako-15	2027	26	185	6-10%	NA	38	Medium risk	24.0	23.3	21.8	19.7	126.7
2017	Shenako-16	2028	27	185	11-25%	NA	38	Medium risk	24.4	23.8	23.6	23.9	119.9
2017	Shenako-21	1984	27	173	11-25%	NA	41	Medium risk	16.6	16.7	17.0	17.1	129.6
2017	Shenako-22	1985	31	170	11-25%	NA	33	High risk	17.3	17.9	17.9	17.1	126.8
2017	Shenako-23	1984	29	190	11-25%	NA	40	Medium risk	17.7	18.1	18.3	17.2	127.0
2017	Shenako-24	1980	25	180	6-10%	NA	41	Medium risk	16.6	16.0	16.1	14.3	164.7
2017	Shenako-25	1979	25	165	6-10%	NA	42	Medium risk	NA	NA	NA	NA	NA
2017	Shenako-26	1979	28	160	11-25%	NA	42	Medium risk	17.5	17.0	13.7	10.9	152.1
2017	Shenako-31	2019	28	178	More than 50%	NA	38	Medium risk	20.2	19.6	19.2	18.9	93.7
2017	Shenako-32	2020	31	159	More than 50%	NA	31	High risk	20.4	19.9	19.9	21.0	94.0
2017	Shenako-33	2020	30	155	More than 50%	NA	31	High risk	20.1	20.2	20.6	20.7	94.9
2017	Shenako-34	2014	31	163	More than 50%	NA	30	High risk	18.6	17.3	17.0	16.8	94.3
2017	Shenako-35	2015	30	150	26-50%	NA	31	High risk	18.4	17.7	17.5	16.9	95.3
2017	Shenako-36	2015	31	153	More than 50%	NA	31	High risk	18.2	NA	19.2	17.7	98.2
2017	Shenako-41	2045	30	186	More than 50%	NA	29	High risk	20.5	20.5	21.2	21.3	92.5
2017	Shenako-42	2047	32	182	More than 50%	NA	29	High risk	19.4	19.8	19.5	19.5	94.8
2017	Shenako-43	2047	30	187	26-50%	NA	29	High risk	19.2	19.2	18.7	18.7	94.9
2017	Shenako-44	2046	34	180	More than 50%	NA	29	High risk	18.0	19.9	20.6	20.6	112.3
2017	Shenako-45	2044	31	172	26-50%	NA	29	High risk	NA	NA	NA	NA	NA
2017	Shenako-46	2043	30	172	More than 50%	NA	29	High risk	NA	NA	NA	NA	88.7
2017	Shenako-51	1943	23	167	More than 50%	NA	43	Medium risk	17.2	17.5	17.5	17.4	95.8
2017	Shenako-52	2011	22	218	6-10%	NA	43	Medium risk	12.8	13.4	13.7	13.8	150.4
2017	Shenako-53	2165	29	225	26-50%	NA	39	Medium risk	18.4	18.2	17.8	17.4	151.9
2017	Shenako-54	2148	22	190	6-10%	NA	40	Medium risk	30.3	29.5	29.1	28.6	148.2
2017	Shenako-55	1933	18	180	2-5%	NA	51	Medium risk	8.8	9.3	10.3	10.4	243.5
2017	Shenako-61	2103	28	166	26-50%	NA	41	Medium risk	27.0	26.8	26.8	26.6	114.3
2017	Shenako-62	2098	33	180	More than 50%	NA	29	High risk	26.7	25.9	25.5	25.0	115.5
2017	Shenako-63	2000	21	184	11-25%	NA	42	Medium risk	14.5	14.3	14.2	14.0	141.8
2017	Shenako-64	1950	25	155	6-10%	NA	40	Medium risk	12.4	13.2	13.8	14.4	119.5

2017	Shenako-65	2079	29	194	More than 50%	NA	37	Medium risk	22.4	22.5	22.4	22.0	110.8
2018	2018-1	2385	19	220	2-5%	0.8	45	Medium risk	8.5	8.0	7.7	7.4	176.2
2018	2018-10	2808	38	275	26-50%	0.7	21	High risk	8.5	10.6	12.6	14.8	107.8
2018	2018-11	2826	35	95	2-5%	0.9	26	High risk	24.7	24.8	25.3	25.7	129.4
2018	2018-12	3011	8	152	1%	0.95	48	Medium risk	22.0	21.6	20.8	19.2	103.5
2018	2018-13	2247	20	205	2-5%	0.95	47	Medium risk	7.0	6.5	6.0	5.4	166.3
2018	2018-14	2002	26	65	6-10%	0.86	40	Medium risk	5.3	5.4	5.3	5.4	202.2
2018	2018-15	1866	15	61	2-5%	0.7	58	Medium risk	1.9	2.1	2.3	2.6	222.8
2018	2018-16	2047	21	200	6-10%	0.7	39	Medium risk	11.1	10.7	10.5	10.2	144.5
2018	2018-17	2005	13	25	non visible	0.8	62	Medium risk	7.3	7.1	7.1	7.9	164.6
2018	2018-18	2208	23	207	26-50%	0.4	39	Medium risk	16.8	17.3	18.2	18.6	99.3
2018	2018-19	2315	33	117	11-25%	0.75	32	High risk	37.9	37.0	36.7	36.0	118.8
2018	2018-2	2419	22	235	1%	0.75	37	Medium risk	5.2	5.1	5.1	5.0	NA
2018	2018-20	2417	26	115	non visible	0.96	39	Medium risk	11.7	11.8	13.0	14.2	290.2
2018	2018-21	2340	29	210	1%	0.97	43	Medium risk	27.4	30.4	31.0	31.6	135.0
2018	2018-22	251	16	174	1%	0.97	43	Medium risk	7.0	7.3	7.5	8.3	168.5
2018	2018-23	2109	2	230	non visible	1	66	Medium risk	1.5	1.5	1.4	1.4	379.8
2018	2018-24	2103	12	314	non visible	1	62	Medium risk	3.4	3.5	3.6	3.7	370.3
2018	2018-25	2097	10	202	non visible	0.99	62	Medium risk	0.9	1.0	1.0	1.0	244.1
2018	2018-26	2315	29	225	6-10%	0.9	48	Medium risk	7.7	8.1	8.3	8.5	213.0
2018	2018-27	2116	32	286	6-10%	0.7	34	Medium risk	15.7	16.9	18.9	20.1	106.2
2018	2018-28	2281	24	152	6-10%	0.7	38	Medium risk	8.5	8.5	8.7	9.1	215.1
2018	2018-29	2383	25	140	26-50%	0.8	38	Medium risk	12.3	11.9	11.6	11.4	167.0
2018	2018-3	2287	41	220	1%	0.87	18	High risk	7.5	7.6	7.6	7.6	258.9
2018	2018-30	2425	25	250	1%	0.99	43	Medium risk	4.6	4.8	4.9	5.2	281.7
2018	2018-31	2383	24	242	non visible	0.95	37	Medium risk	10.1	9.7	9.4	9.2	153.8
2018	2018-32	2936	31	139	11-25%	0.9	23	High risk	23.2	23.1	23.0	22.8	122.2
2018	2018-33	2969	21	221	11-25%	0.5	28	High risk	12.5	11.9	11.6	11.5	93.4
2018	2018-34	2792	7	147	non visible	0.98	52	Medium risk	1.3	1.3	1.5	1.6	115.8

2018	2018-35	2632	27	275	6-10%	0.7	36	Medium risk	3.4	3.4	4.8	6.0	115.0
2018	2018-36	2451	22	22	non visible	0.99	46	Medium risk	6.8	6.7	6.6	6.4	234.3
2018	2018-37	2808	45	155	6-10%	0.7	14	High risk	41.6	35.0	37.1	38.8	93.4
2018	2018-38	2187	7	201	1%	0.9	57	Medium risk	2.4	2.8	3.0	3.5	175.7
2018	2018-39	2100	21	240	2-5%	0.99	43	Medium risk	3.1	3.0	3.0	2.9	303.6
2018	2018-4	2175	15	270	non visible	0.9	51	Medium risk	6.1	6.3	6.3	6.3	236.3
2018	2018-5	2873	25	65	6-10%	0.8	36	Medium risk	12.8	12.8	13.3	13.7	96.4
2018	2018-52	2481	20	90	More than 50%	0.4	63	Medium risk	17.3	16.6	15.3	14.4	120.5
2018	2018-53	2389	32	290	More than 50%	0.25	42	Medium risk	21.0	21.0	21.1	20.9	121.2
2018	2018-54	2479	28	45	11-25%	0.75	43	Medium risk	18.4	18.5	17.2	16.0	192.8
2018	2018-55	2601	32	130	11-25%	0.9	37	Medium risk	15.7	16.4	17.0	18.0	198.2
2018	2018-56	2538	13	165	More than 50%	0.2	44	Medium risk	9.1	10.7	12.4	13.3	143.0
2018	2018-57	2585	30	285	2-5%	0.9	24	High risk	1.5	2.8	4.2	6.5	146.7
2018	2018-58	2549	17	280	6-10%	0.65	66	Medium risk	6.9	7.0	7.6	8.4	169.5
2018	2018-59	2440	12	240	11-25%	0.85	58	Medium risk	8.3	8.2	8.6	8.9	267.3
2018	2018-6	2840	3	15	2-5%	0.8	63	Medium risk	3.7	3.8	3.9	4.0	132.5
2018	2018-60	2570	22	180	26-50%	0.75	42	Medium risk	15.1	15.0	14.3	13.5	194.2
2018	2018-61	2601	12	300	2-5%	0.98	59	Medium risk	9.9	9.8	9.9	9.8	153.9
2018	2018-62	2693	25	160	2-5%	0.95	48	Medium risk	3.8	3.6	3.6	3.6	153.3
2018	2018-63	2816	21	212	2-5%	0.95	41	Medium risk	8.3	8.1	7.9	7.8	219.8
2018	2018-64	2921	12	308	1%	0.7	46	Medium risk	4.3	4.5	4.7	4.7	127.8
2018	2018-65	2890	10	72	1%	0.95	53	Medium risk	3.6	5.2	7.1	8.1	112.2
2018	2018-66	2903	6	3	26-50%	0.95	59	Medium risk	1.2	1.2	1.2	1.3	118.6
2018	2018-67	2898	21	195	More than 50%	0.45	29	High risk	23.3	22.6	21.5	19.9	97.9
2018	2018-68	2551	21	186	More than 50%	0.25	33	High risk	13.1	12.7	12.5	12.1	128.8
2018	2018-69	2109	25	105	1%	0.9	43	Medium risk	7.9	8.0	7.8	7.7	283.0
2018	2018-7	2511	25	50	non visible	0.95	41	Medium risk	14.1	13.7	13.6	13.4	150.9
2018	2018-70	2242	19	8	non visible	1	57	Medium risk	4.8	4.5	4.3	4.2	244.1
2018	2018-71	1845	3	140	non visible	0.98	59	Medium risk	0.4	0.4	0.3	0.3	213.5

2018	2018-72	1840	8	25	non visible	0.99	68	Low risk	1.3	1.2	1.3	1.2	387.2
2018	2018-73	1862	8	270	non visible	0.98	61	Medium risk	0.2	0.2	0.2	0.2	287.5
2018	2018-74	1859	9	35	non visible	0.95	70	Low risk	0.7	0.7	0.7	0.7	175.5
2018	2018-75	1762	32	202	More than 50%	0.4	28	High risk	80.0	64.2	53.9	51.2	84.5
2018	2018-76	1680	24	195	More than 50%	0.55	38	Medium risk	74.9	74.3	64.5	60.4	87.2
2018	2018-77	1653	21	66	non visible	0.98	49	Medium risk	8.3	8.9	9.6	9.7	143.8
2018	2018-78	1843	15	230	non visible	0.98	46	Medium risk	7.5	7.6	7.8	8.0	232.2
2018	2018-79	1808	38	212	More than 50%	0.6	28	High risk	5.9	5.4	5.3	5.4	172.5
2018	2018-8	2447	5	235	non visible	0.98	56	Medium risk	3.7	3.9	4.2	4.4	264.3
2018	2018-80	1889	20	164	11-25%	0.75	49	Medium risk	10.1	10.2	10.0	9.7	113.3
2018	2018-81	2016	42	194	More than 50%	0.3	22	High risk	28.1	26.8	26.3	28.9	98.9
2018	2018-82	2046	31	140	More than 50%	0.6	33	High risk	15.7	15.8	15.8	16.1	96.5
2018	2018-83	2054	40	232	More than 50%	0.4	21	High risk	22.6	22.2	21.9	21.4	91.8
2018	2018-84	2011	39	181	More than 50%	0.4	29	High risk	22.2	22.3	22.6	22.6	108.6
2018	2018-85	1926	14	79	non visible	0.95	56	Medium risk	6.0	6.7	7.6	8.6	125.5
2018	2018-86	1866	35	170	More than 50%	0.5	30	High risk	20.9	20.9	20.6	20.6	105.7
2018	2018-87	2121	18	59	1%	0.95	56	Medium risk	5.4	4.9	4.9	4.9	188.9
2018	2018-88	2242	14	30	6-10%	0.98	58	Medium risk	6.1	6.3	6.4	6.4	295.8
2018	2018-89	2203	17	117	non visible	0.98	49	Medium risk	6.9	7.2	7.3	7.3	222.8
2018	2018-9	2047	39	220	More than 50%	0.4	29	High risk	15.0	14.9	14.7	14.5	102.2
2018	2018-90	2098	10	92	non visible	0.97	66	Medium risk	7.9	8.4	8.6	8.7	165.8
2018	2018-91	2096	28	150	11-25%	0.9	43	Medium risk	4.8	5.6	6.2	6.9	147.8

Integrated Biodiversity Management,
South Caucasus, IBiS

Programme office Georgia
Ministry of Environmental Protection and Agriculture of Georgia

6 Gulua Str.
0114 Tbilisi, Georgia
T +995 322 201828
www.giz.de
www.biodivers-southcaucasus.org

Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) GmbH