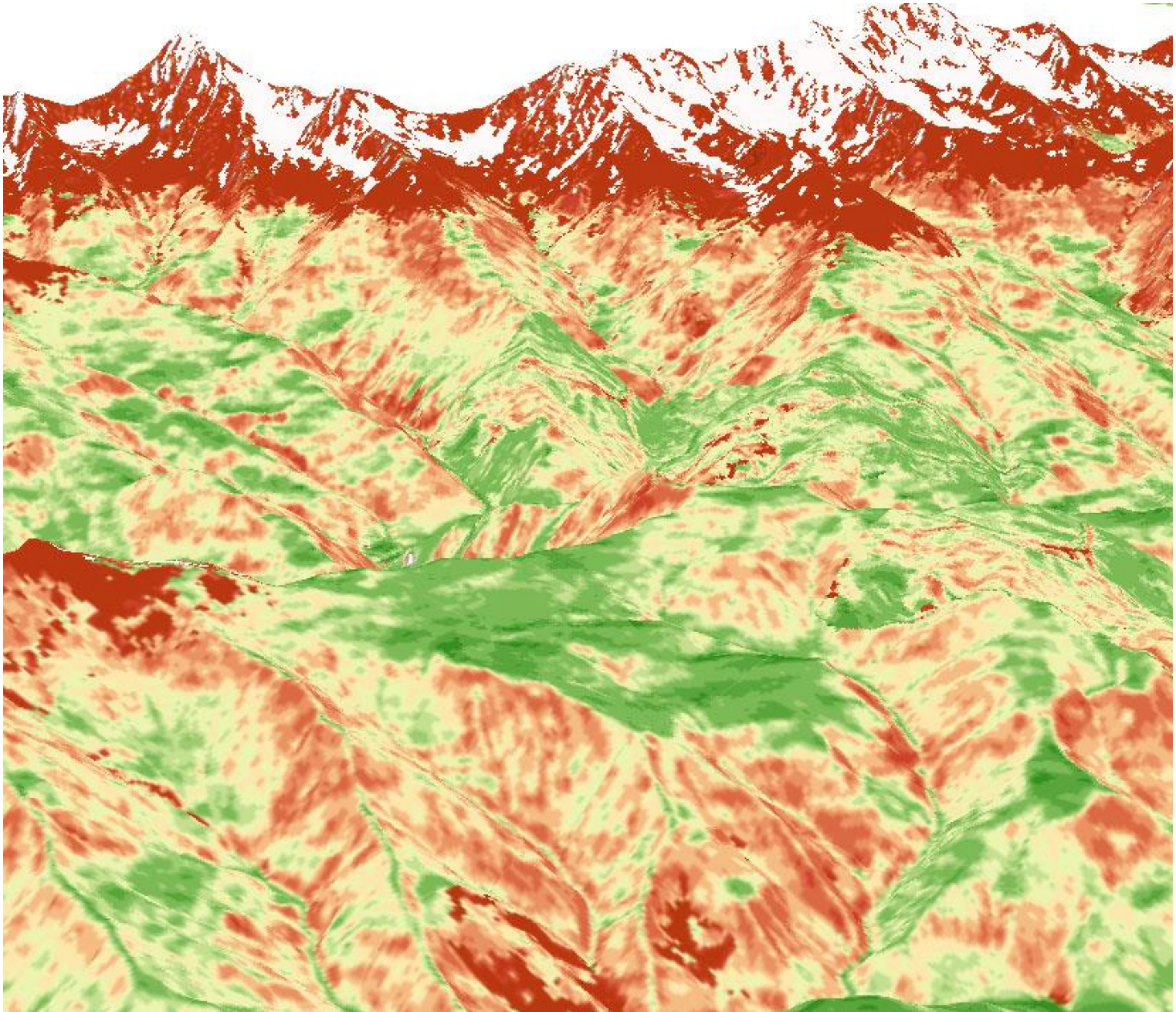

DEVELOPMENT OF LAND COVER AND EROSION RISK MAP BASED ON REMOTE SENSING FOR TUSHETI PROTECTED AREAS

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SOIL EROSION MODELING

Soil erosion is a worldwide environmental problem that degrades soil productivity and water quality, causes sedimentation and increases the probability of agricultural land degradation. Erosion control requires a quantitative and qualitative evaluation of potential soil erosion on a specific site, and the knowledge of terrain information, soils, land use system and management practices. Revised Universal Soil Erosion Equation (RUSLE) is widely used to estimate soil erosion.

This study has applied Geographical Information System (GIS) and Revised Universal Soil Loss Equation (RUSLE) to predict the annual average soil loss rate in Tusheti Area (East-north Georgia)

To achieve the goals, the RUSLE factors were calculated using the local and global data. The soil data used to develop the soil erodibility factor (K), and Digital Elevation model of the study area was used to generate the topographical factor (LS). The values of cover-factor (C) was estimated from satellite image. The rainfall-runoff erosivity (R) was derived from monthly rainfall data and Fourier index.

The model represents how climate, soil, topography, and land use affect rill and gully soil erosion caused by raindrop impact and surface runoff. It has been extensively used to estimate soil erosion loss, to assess soil erosion risk, and to guide development and conservation plans in order to control erosion under different land-cover conditions, such as pasture lands and disturbed forest lands. (Environmental GIS: Lab 10)

The RUSLE is expressed as:

$$A=R*K*LS*C*P$$

Where:

A = Soil loss per unit of area, t ha-1;

R = Rainfall-runoff erosivity factor, MJ ha-1 mm h-1;

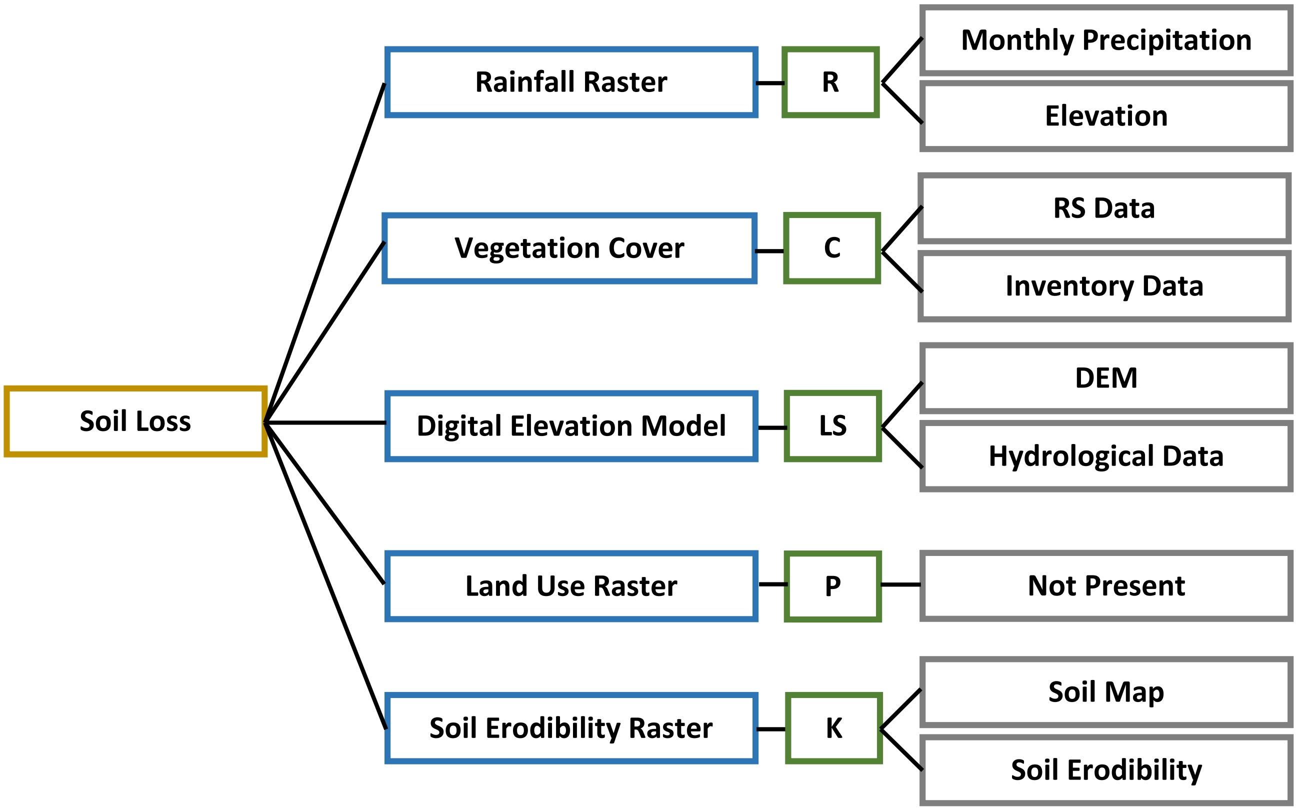
K = Soil erodibility factor (t ha-1)/(MJ ha-1 mm h-1);

L = Slope length factor

S = Slope factor

C = Cover-management factor

P = Conservation practice factor



Rainfall erosivity factor (R Factor)

R is a measure of erosivity of rainfall which is the product of storm kinetic energy and maximum 30 minute intensity EI_{30}. When other factors are constant, storm losses from rainfall are directly proportional to the product of total kinetic energy of the storm (E) times its 30 minute intensity (I_{30}). (Arnoldus, 1978)

Data

We used a CHELSA (Climatologies at high resolution for the earth's land surface areas) high resolution (1 km) climate data, which covers whole Tusheti area. The source of data is www.chelsa-climate.org. The climate data includes monthly mean precipitation pattern and covers a total of 34 years, between 1979 and 2013. This climate data includes incorporation of topo-climate (e.g. orographic rainfall & wind fields).

The data is based on a quasi-mechanistical statistical downscaling of the ERA-interim global atmospheric analysis produced by the EuropeanCentre for Medium-Range Weather Forecasts (www.ecmwf.int). ERA-interim model uses radiance data from all available satellites, scatterometer wind data and many other axillary data.

Estimation of R-factor

R-factors links to rainfall and runoff erosion index. R-factor is defined as a sum of individual storm EI-values (abbreviation for energy multiplied by the maximum intensity in 30 min) for a year averaged over long time periods (more than 20 years) to accommodate apparent cyclical rainfall patterns. However, this calculation of R-factor requires daily climatic data (extracted from pluviograms) which cover a longer period of time.

Unfortunately, there is only one meteorological station in the Tusheti area. First, it is impossible to estimate R-factor as described before due to the lack of longer period of time data. Second, interpolation of the rainfall data to whole area from one station will greatly compromise accuracy.

However, regional rainfall erosivity can be estimate based on the Fournier index modified by Arnoldus (1980) by using monthly and annual precipitation data:

$$\mathrm{F} = \sum_{i=0}^{12} \left(\frac{P_i^2}{P}\right) \text{ [1],}$$

where P_i is the monthly average amount of precipitation for month i (mm), P is the average annual quantity of precipitation (mm).

Erosivity class	**F**
Verry low	0 - 60
Low	60 – 90
Moderate	90 - 120
Severe	120 - 160
Very severe	> 160
Extremely severe	

Table 1. The erosivity classes by modified Fournier index (F).

There are a several equations to transfer the Fournier Index (F) to the R-factor (R) described in the papers. Each of equations have a limitations in predicting R-factor values. We tried several relations between F and R. Finally, we used next equation, which were presented in the paper of Kenneth G. Renard et al. (1994):

$$R_{factor}=0.07397F^{1.847}\text{[2]}$$

Results:

Figure 1. Fournier Index (1979-2013) for the Tusheti area.

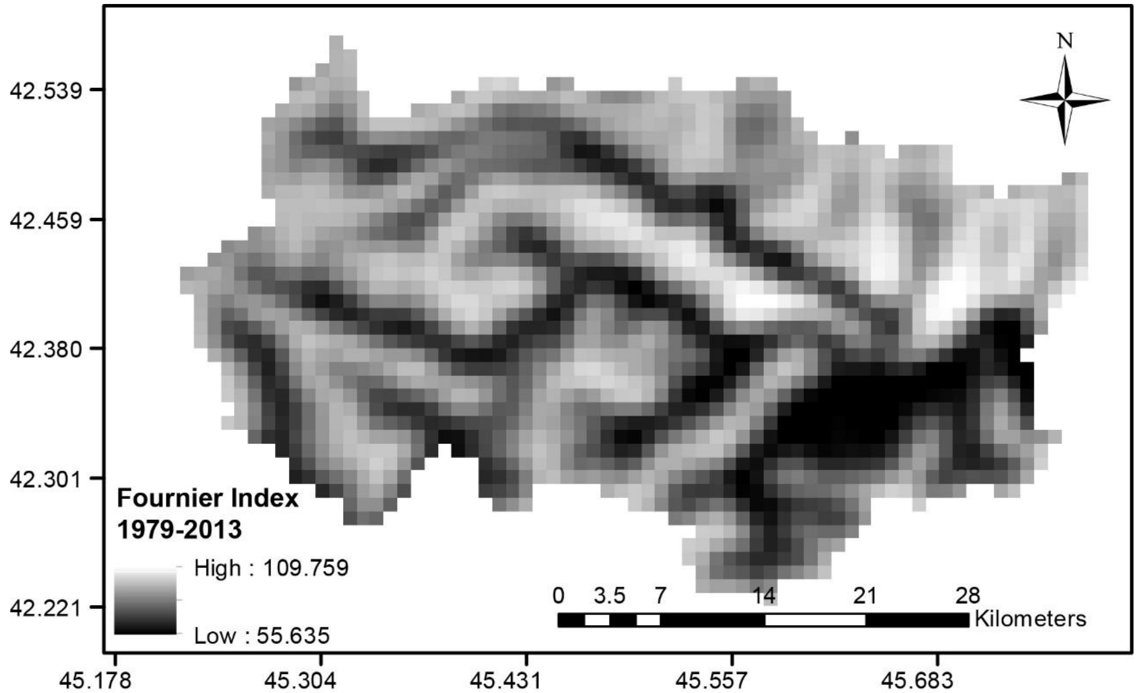
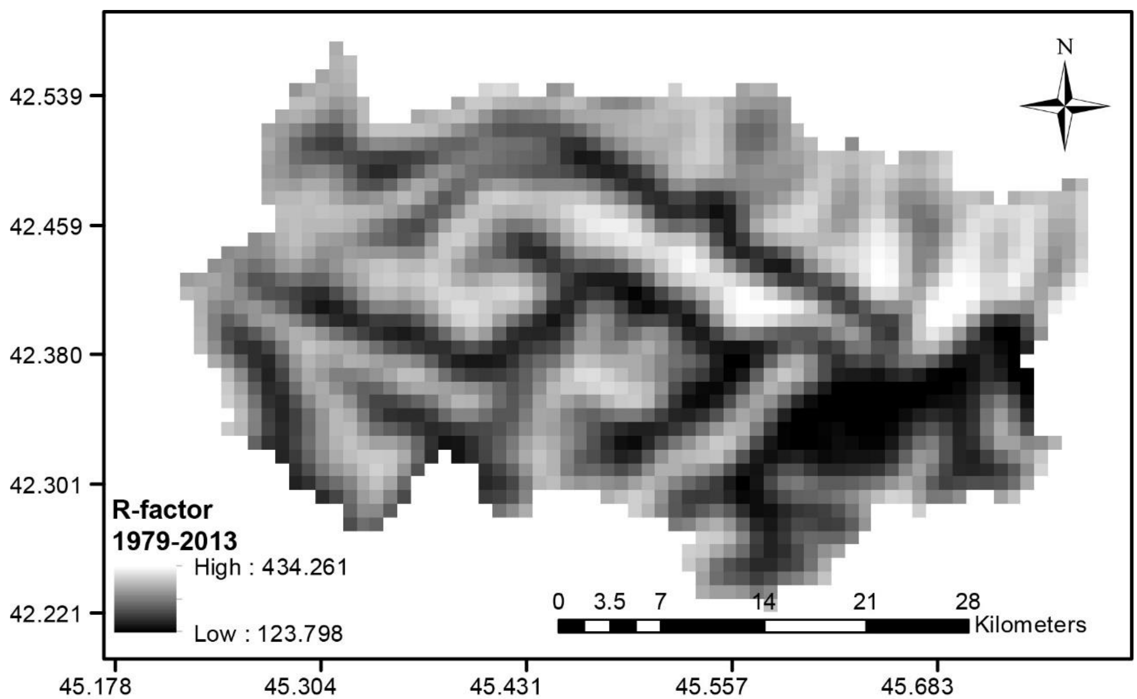


Figure 2. R-factor based on Fournier Index (1979-2013) for the Tusheti area.



Soil Erodibility index (K Factor)

Soil erodibility factor represents both susceptibility of soil to erosion and rate of runoff, as measured under the standards unit plot condition. The value of this factor is affected by infiltration capacity and structural stability of the soil.

So, the K value run from 1.0 to 0.01 with the highest values for soils with high content of silt or very find send. For example, soils high in clay have low K value, about 0.05 to 0.15, because they resistant to detachment.

Coarse textured soils, such as sandy soils, have low K values about 0.05 to 0.2, because of low runoff even though these soils are easily detached.

Medium textured soils, such as the silt loam soils, have a moderate K values, about 0.25 to 0.04, because they are moderately susceptible to detachment and they produce moderate runoff.

Soils having high silt content are most erodible of most soils. They are easily detached: tend to crust and produce high rates of runoff. Values of K for these soils to be greater than 0.4 (Weesies A)

The Soil erodibility factor was calculated using the soil properties obtained from Georgian Agriculture University Soil-lab by using equation 1 given by (Wischmeier and Smith 1978). This equation was settled upon due to availability of data on soil structure, organic matter and permeability. The equation reads as shown below:

$$K = 2.1x10^{-6} \times M^{1.14} (12\text{-}OM) + 0.025 (S\text{-}3) + 0.0325 (P\text{-}2)$$

Where;

K = soil erodibility factor in t.h/MJ.mm

M = (Percentage very fine sand + Percentage silt) × (100 – Percentage clay)

OM = Percentage of organic matter

S = Code according to the soil structure (very fine granular = 1, fine granular = 2, coarse granular = 3, lattice or massive = 4), and P = Code according to the permeability/drainage class (fast = 1, fast to moderately fast = 2, moderately fast= 3, moderately fast to slow = 4, slow = 5, very slow = 6) (Wischmeier and Smith 1978)

1:200,000 scale soil map was used for stratification of K factor. Composed map was rasterized and splined for avoiding sharp boundaries between soil classes.

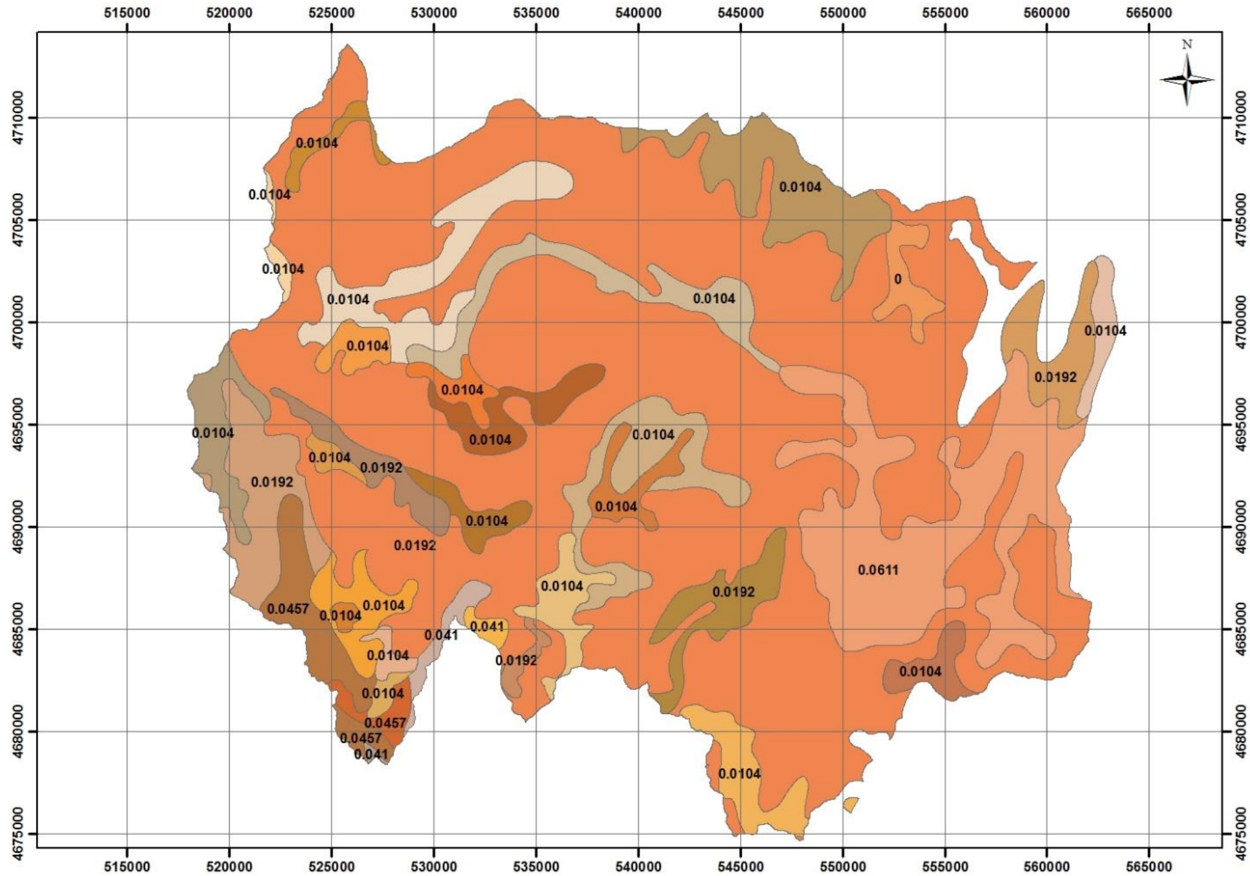


Fig 3. Vector Soil map of Tusheti area

Slope and Slope length (LS) Factor

The LS-factor is a combination of the effects of slope length and slope steepness on the erosion of a slope. The calculation LS topographic factor on a grid is using Digital Elevation Model (DEM) and applying to each pixel in the DEM. DEM provides necessary basic information about terrain, slope, aspect, drainage area and network. However, in the beginning it is necessary to fill any spurious single-cell nodata cells and sinks within the source DEM data by using an interactive routine.

Desmet and Govers (1997) proved LS-factor model which is appropriate for landscape-scale soil erosion modeling, and can capture complex topography, due to slope steepness is not uniform for the whole area.

Desmet and Govers (1996) proposed a two-dimensional terrain using the concept of the unit-contributing area:

$$L_{i,j} = [(A_{i,j} + D^2)^{m+1} - (A_{i,j})^{m+1}]/[(D)^{m+2} * (x_{i,j})^m * (22.13)^m] \quad [1]$$

where $A_{i,j}$ is the contributing area at the inlet of grid cell (i,j) measured in m^2. D is the grid cell size (meters), $x_{i,j} = \sin a_{i,j} + \cos a_{i,j}$, the $a_{i,j}$ is the aspect direction of the grid cell (i,j).

m is related to the ratio β of the rill to interill erosion:

$$m = \beta/\beta+1 \quad [2]$$

where ,

$$\beta = \sin\theta/0.0896/[\,0.56 + 3*(\sin\theta)^{0.8}] \quad [3]$$

θ is the slope angle in degrees. The m ranges between 0 and 1, and approaches 0 when the ratio of rill to interill erosion is close to 0.

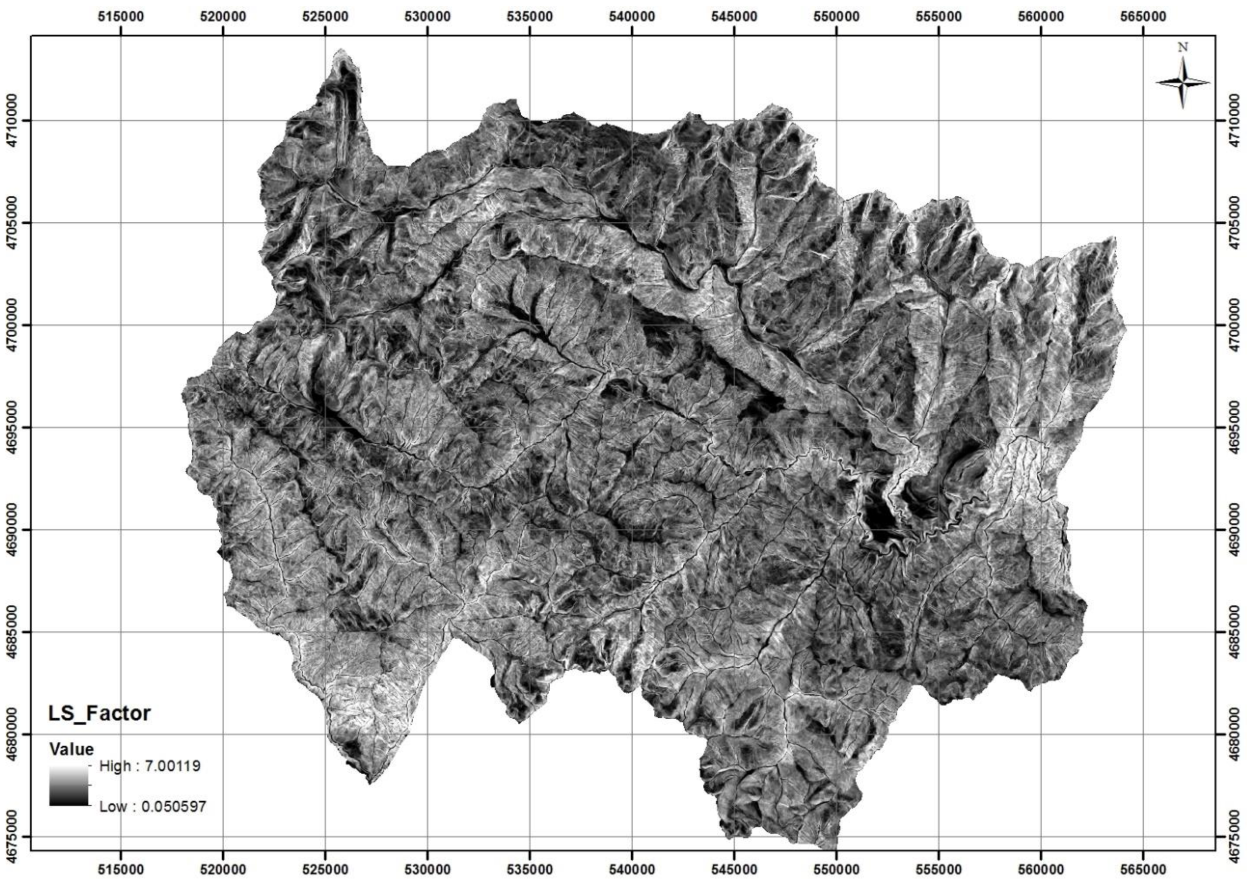


Fig 4. Raster map of LS factor

Cover management factor (C)

Method to estimate C-factor. C-factors links to the cover-management characteristics and represents the effect of surface cover and roughness on soil erosion. C-factor depends on vegetation type, stage of growth and cover, because vegetation cover protects the soil by dissipating the raindrop energy before reaching soil surface. For example, nearly exposed soil has a C-factor value near one then when protected soil has a C-factor value near zero (Toy et al., 1999). Since NDVI values have correlation with C-factor (De Jong et al., 1999) many researchers used regression analysis to estimate C-factor values for land cover.

First of all we applied algorithm which allows calculation of Bottom Of Atmosphere (BOA) reflectance from Top Of Atmosphere (TOA) reflectance images available in Level-1C products to the Sentinel-2 data. Then, we calculated *Normalized Difference Vegetation Index (NDVI) and Red Edge Normalized Difference Vegetation Index* (*reNDVI*) based on near infra-red (NIR), red edge (RE) and red (R) bands.

NDVI=(NIR-R)/(NIR+R)

reNDVI=(RE+R)/(RE-R)

reNDVI is more sensitive to the different type of vegetation than NDVI. So for our further analysis, we chose reNDVI to approximate C-values using next provisional formula (Van der Knijff et al., 2000):

$$C = \exp[-a\frac{reNDVI}{(b - \mathrm{re}NDVI)}]$$

a, b are parameters that determine the shape of the reNDVI-C curve. An a-value of 2 and a b-value of 1 seem to give reasonable results (Van der Knijff et al., 1999).

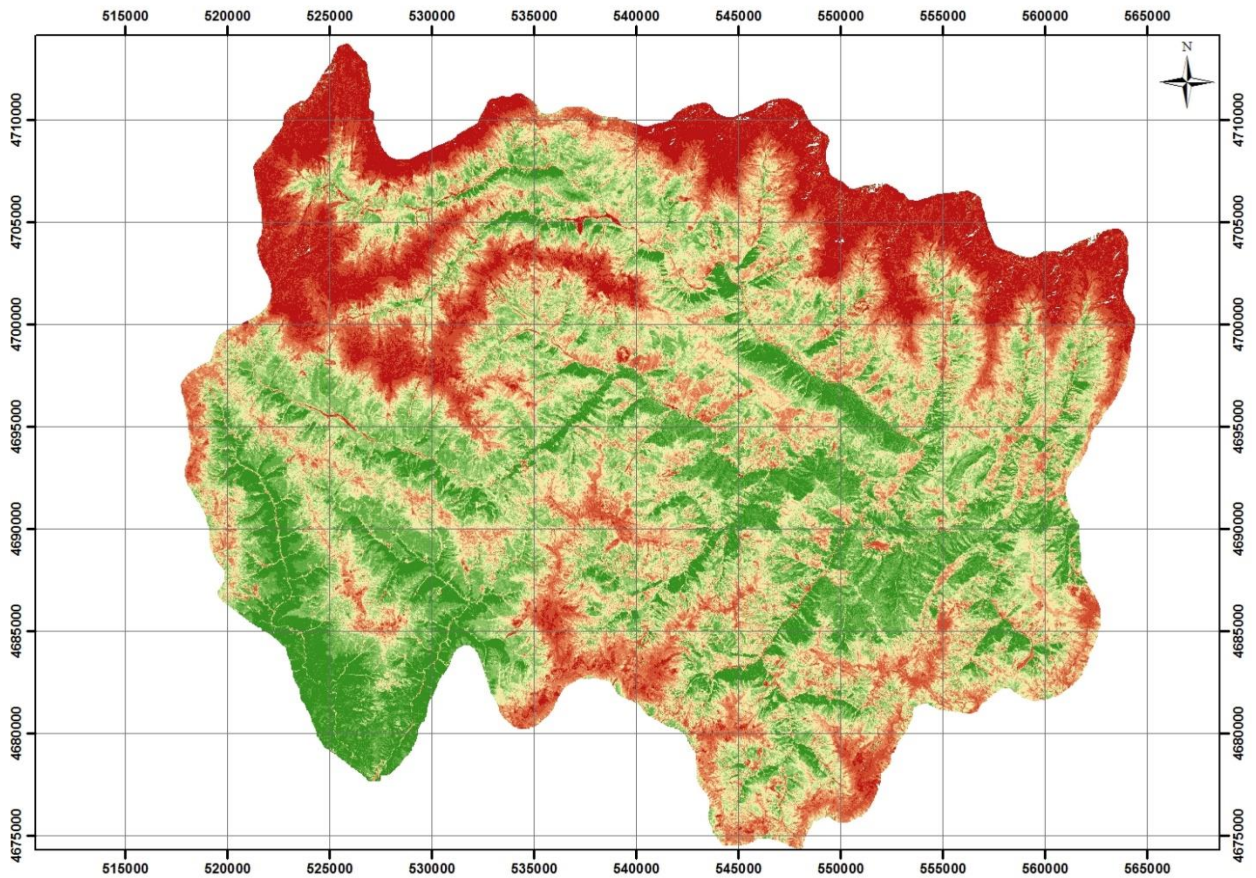


Fig 5. Raster map of C factor

The Support Practice (P Factor)

The support Practice is the support or land management practice factor. In RUSLE, the support practice factor is generally applied to disturbed lands and represents how surface and management practices such as contouring, terracing and strip cropping are used to reduce soil erosion. For areas where is no support practice the P factor is set to 1 (Simms A.D 2003). Tusheti area have no support practice, or it's no applicable to the model, so we set P to 1.

Support practice factor (P-factor) is rarely taken into account in soil erosion risk modeling at large area, as it is difficult to estimate it with a high accuracy. Different types of practice techniques are known in agriculture, but in Tusheti only historical remnants of terraces are presented that became parts of the natural terrain.

To refine the current model the detailed DEM (Digital elevation model) is needed. Existing 1:25,000 scale DEM is not accurate and sensitive enough for such small elevation change. Therefore, for receiving better results we recommend to use more detailed DEM (Approx. 1-2m accuracy), which unfortunately is not available for the project at this moment.

Accuracy Assessment

Assessments of the accuracy of RUSLE are impeded by many factors. Field studies are costly, labor intensive, and time consuming, which may lead to few replications. Variability in data caused by differences in plot preparation or soil characteristics can result in misleading conclusions. It is hard to find hillslopes without variation in soil properties where numerous tests can be replicated (Foster et al., 1999).

The final result of this study was compared to results from different countries (European Communities) and concluded that the overall results of this study is in an acceptable range.

LAND COVER CLASSIFICATION

Land cover corresponds to a physical description of space, the observed (bio) physical cover of the earth's surface (DI GREGORIO & JANSEN 1997). It is that which overlays or currently covers the ground. This description enables various biophysical categories to be distinguished - basically, areas of vegetation (trees, bushes, fields, lawns), bare soil (even if this is a lack of cover), hard surfaces (rocks, buildings) and wet areas and bodies of water (sheets of water and watercourses, wetlands).

The survey territory of Tusheti has particularly diverse landscape, and what is more, the terrain, what causes certain problems with the use of Remote Sensing data, specifically in the creation of land cover. It should be mentioned in the very first place, that Tusheti active terrain (difference in altitudes and sloping flanks) creates shaded sections, which are "no data" areas for optical satellites. Of course, there are different satellite image processing methods, which allow for the illumination of shadows on the image. These statistic methods are widely used in cases, when there are digital altitude models of higher resolution that that of the image, with the help of which models the darkened pixels can be corrected. Unfortunately there are no such accurate data for Tusheti territory.

The mention should also be made of the impact of rock sloughing on decoding of some classes of grasslands, as such mixed areas often create certain spectral noise, complicating the classification process.

In the course of supervised classification of satellite images, the reference data are being used; e.g. GPS coordinates, which describe land cover types. The absence of such data further complicates the interpretation process.

Data and Methodology

Based on the above factors it was decided to use the following type of satellite image and classification algorithm.

Sentinel-2 is an Earth observation mission developed by ESA as part of the Copernicus Programme to perform terrestrial observations in support of services such as forest monitoring, land cover changes detection, and natural disaster management.

The Sentinel-2 mission has the following capabilities:

- Multi-spectral data with 13 bands in the visible, near infrared, and short wave infrared part of the spectrum

- Systematic global coverage of land surfaces from 56° S to 84° N, coastal waters, and all of the Mediterranean Sea
- Revisiting every 5 days under the same viewing angles. At high latitudes, Sentinel-2 swath overlap and some regions will be observed twice or more every 5 days, but with different viewing angles.
- Spatial resolution of 10 m, 20 m and 60 m
- 290 km field of view
- Free and open data policy

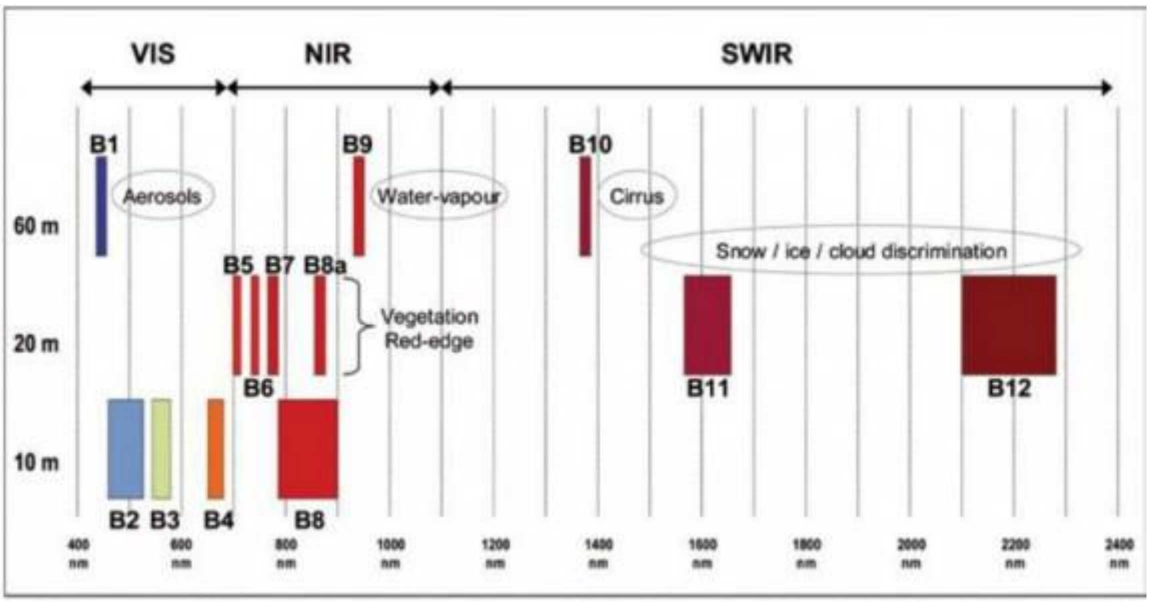


Fig 6. Sentinel-2 spectral bands

SVM-Support Vector Machine

Support Vector Machine (SVM) is a supervised classification method derived from statistical learning theory that often yields good classification results from complex and noisy data. It separates the classes with a decision surface that maximizes the margin between the classes. The surface is often called the optimal hyperplane, and the data points closest to the hyperplane are called support vectors. The support vectors are the critical elements of the training set. (Harris Geospatial Center).

Image Classification

Pre classification

We applied the atmospheric, terrain and cirrus correction of Top-Of-Atmosphere to the downloaded Level-1C data by using Sen2Cor processor in SNAP (Sentinel Application Platform:

http://step.esa.int/main/snap-2-0-out-now/). Using Sen2Cor application Bottom-Of-Atmosphere corrected reflectance image (Level-1A) was created.

Classification

Although we lacked field data of land cover types, we applied Jeffries-Matusita, Transformed Divergence algorithm for the reliability of training classes and their separation, with the help of which algorithm the training pixels with homogeneous spectral characteristics were identified. Finally, we compiled the following raster samples: 9-Grassland; 4-Deciduous Forest; 2 Coniferous forest; 1-Shrubland; 1-Bare soil; 1-Scree; 1-Shadows; 1-Clouds and 1-Permanent snow.

We applied Support Vector Machine Classification algorithm, for which algorithm we used the following parameters:

- Kernel type: Polynomial
- Degree of Kernel Pol: 2
- Bias in Kernel Function: 1
- Penalty Parameter: 500

Post Classification

Although the classes were separated spectrally, it deemed impossible to identify them without field data, hence in order to avoid thematic errors, we amalgamated thematically similar types of classes.

E.g. from 9 grassland only one was left, one from 4-Deciduous Forest, etc.

In the course of post-classification the image pixels were aggregated, when independent pixels were joined with nearby largest classes, as a result of which process the land cover was cleaned from surplus speckles and noises.

According to contract terms we had to establish 4 classes of grassland apart from classic land cover types, however extending field data of only Gometsari gorge to whole Tusheti would have resulted in major error, hence we generated NDVI - Normalized Difference Vegetation Index and conditionally isolated four classes with different grassland biomass (high biomass, medium biomass, low and very low biomass). See land cover map.

For quantitative assessment of grassland biomasses collected in the field and for their mapping on the example of only Gometsari gorge see the next chapter, p.

Accuracy assessment

Land cover accuracy assessment is done on the basis of field data, however in our case no such data were available and hence the verification was done only on the basis of old, more detailed satellite image and old 1959-60 topographic map with 1:25,000 scale, what was of more visual, than statistic type.

We hope, that during the next phases of the project the Ground truthing points of field data will be taken and drawn map will be verified and improved using relevant statistic methodology.

Spatial accuracy and scale of the land cover depends on the resolution of the initial satellite image, with 10m pixel size, what allows for the creation of only 1:25,000 scale map.

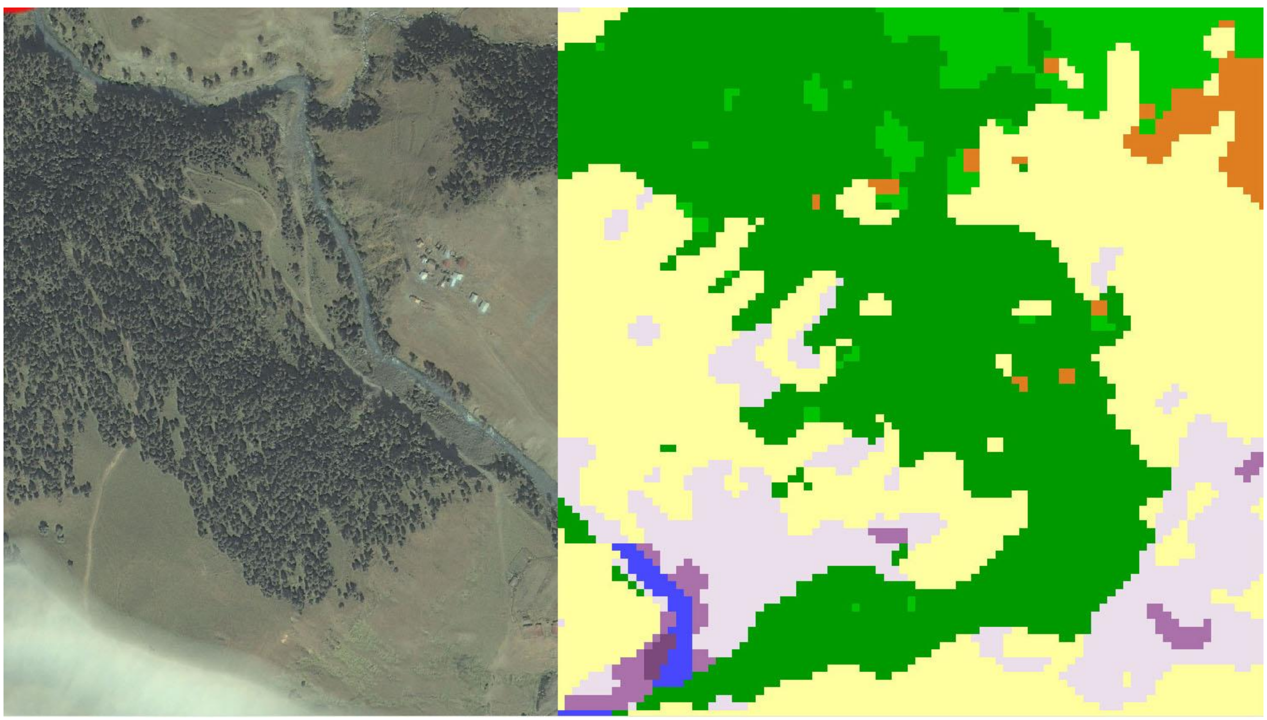


Fig 7. Comparison between 1m (IKONOS) and 10 m LandCover data

Data

We used multi-spectral and high resolution remote sensing data from the Sentinel-2 mission. These data have a free access and could be regularly downloading on the Sentinels Scientific Data Hub site (https://scihub.copernicus.eu/).

The Sentinel-2 Multispectral Instrument (MSI) acquires 13 spectral bands. Visible and visible near-infrared (VNIR) portion of the electromagnetic spectrum has resolution 10 metres: Band2 (490 nm), Band3 (560 nm), Band4 (665 nm) and Band8 (842 nm). Spatial resolution 20 meters have next six bands: Band5 (705 nm), Band6 (740 nm), Band7 (783 nm), Band8a (865 nm), Band11 (1610 nm) and Band12 (2190 nm), where Band11 and Band 12 are Short-wave infrared bands. Band1 (443 nm), Band9 (940 nm) and Band10 (1375 nm) have 60 m spatial resolution.

Sentinel-2 Bands	Central Wavelength (µm)	Resolution (m)
Band 1 - Coastal aerosol	0.443	60
Band 2 - Blue	0.490	10
Band 3 - Green	0.560	10
Band 4 - Red	0.665	10
Band 5 - Vegetation Red Edge	0.705	20
Band 6 - Vegetation Red Edge	0.740	20
Band 7 - Vegetation Red Edge	0.783	20
Band 8 - NIR	0.842	10
Band 8A - Vegetation Red Edge	0.865	20
Band 9 - Water vapour	0.945	60
Band 10 - SWIR - Cirrus	1.375	60
Band 11 - SWIR	1.610	20
Band 12 - SWIR	2.190	20

Due to the necessarily to use combination of the different bands with different resolution, we applied a resampling (SNAP Toolbox) and used resolution 10 meter. The scale of output map could be estimate based on this resolution, as suggested Waldo Tobler in 1987. For instance, if the raster resolution is 10 meter, than the resolution double and multiply to 1000. Accordingly, the estimated map scale will be 1:20,000.

Remote sensing data with Level-1C (top of atmosphere reflectance) were downloaded, where the granules are 100x100 km^2 in UTM/WGS84 projection. These products contain applied radiometric and geometric corrections (including ortho-rectification and spatial registration).

Sentinel-2 data acquisition time (5 August 2016) was selected according to the time at which the field data were sampled (in the beginning of August 2016) to observe approximately same state for the vegetation.

The aboveground oven-dry-weight of grass can be measured directly by collecting all plants on the square meter area, oven-drying all components and then weighing them. This procedure was done in the 28 places of the grasslands and pastures in the area around Tusheti, Gometsari gorge (with villages Dochu, Beghela, Jvarboseli and Verkhovani). Please, see the distribution of the samples on the figure N.

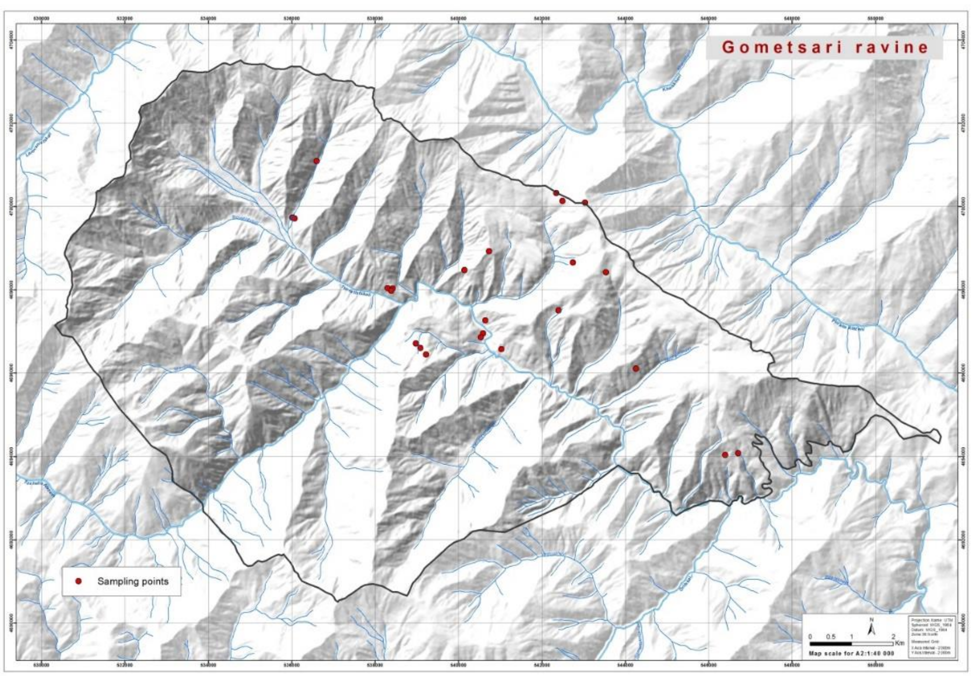


Fig 8. Distribution of samples from field trip.

One by one meter square samples were taken randomly within 10 by 10 meter square. The GPS coordinates were given of the upper left corner of the 10 by 10 meter square areas. Orientation of samples areas were taken randomly also.

Methods

We applied the atmospheric, terrain and cirrus correction of Top-Of-Atmosphere to the downloaded Level-1C data by using Sen2Cor processor in SNAP (Sentinel Application Platform: http://step.esa.int/main/snap-2-0-out-now/). Sen2Cor creates Bottom-Of-Atmosphere corrected reflectance image (Level-1A). Then, we used this image to calculate different Vegetation indices and biophysical parameters in the SNAP such as NDVI (Normalized Difference Vegetation Index), *Red Edge NDVI (rNDVI), LAI (Leaf Area Index) and* leaf chlorophyll content *(LAI_cab), FAPAR (Fraction of Absorbed Photosynthetically Active Radiation).*

LAI_cab parameter, which control physical and physiological processes in vegetation canopies, shows much better correlation with dry biomass obtained from the field trip than others parameters. Therefore, we decided to use this parameter and dry biomass estimation from the field trip to create a linear regression model.

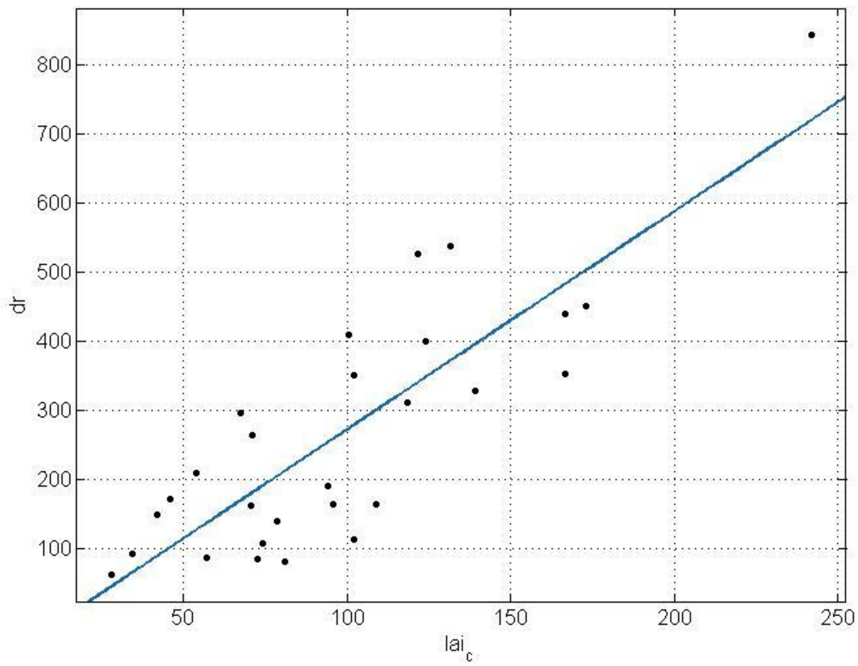
So, the distribution of the Gometsari gorge dry biomass was obtained from LAI_cab parameter and field trip measurements of the dry biomass by using linear regression models of different degrees (1, 2) and multi-variables linear regression model of degree1. The product of biomass ton per hectare for a given strata and the corresponding area will result in an estimate of the total biomass for the region.

1) Linear model Polynomial (Degree 1):

$$DR\_W(LAI\_cab) = p1*LAI\_cab + p2 \ [1],$$

where p1 = 3.153, p2 =-43.23

Goodness of fit: R^2: 0.7002, Adjusted R^2: 0.6886, RMSE: 101.7

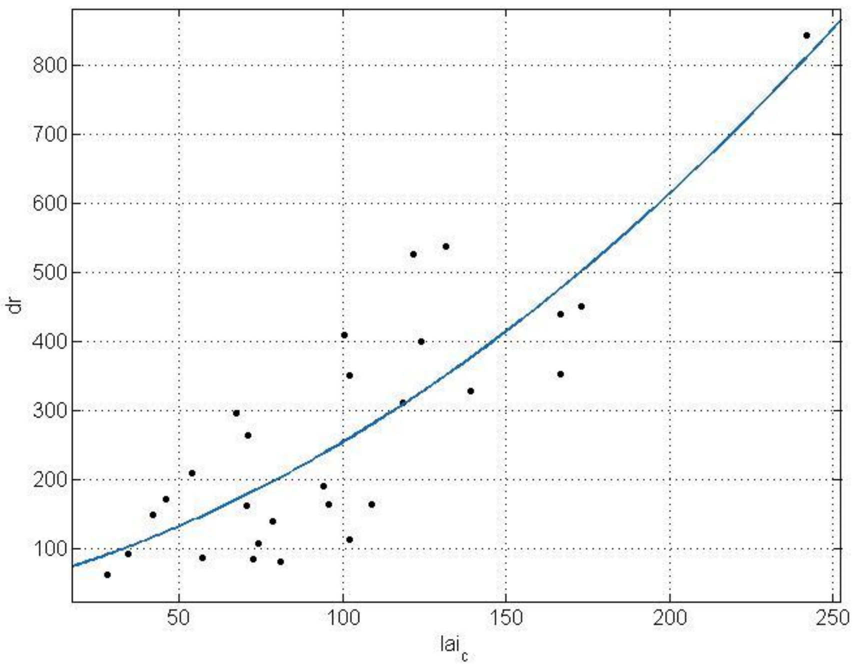


2) Linear model Polynomial (Degree 2):

DR_W(LAI_cab) = p1*LAI_cab^2 + p2*LAI_cab + p3 [2],

where p1 = 0.007844, p2 =1.247, p3 =50.78

Goodness of fit: R^2: 0.7204, Adjusted R^2: 0.698, RMSE: 100.1

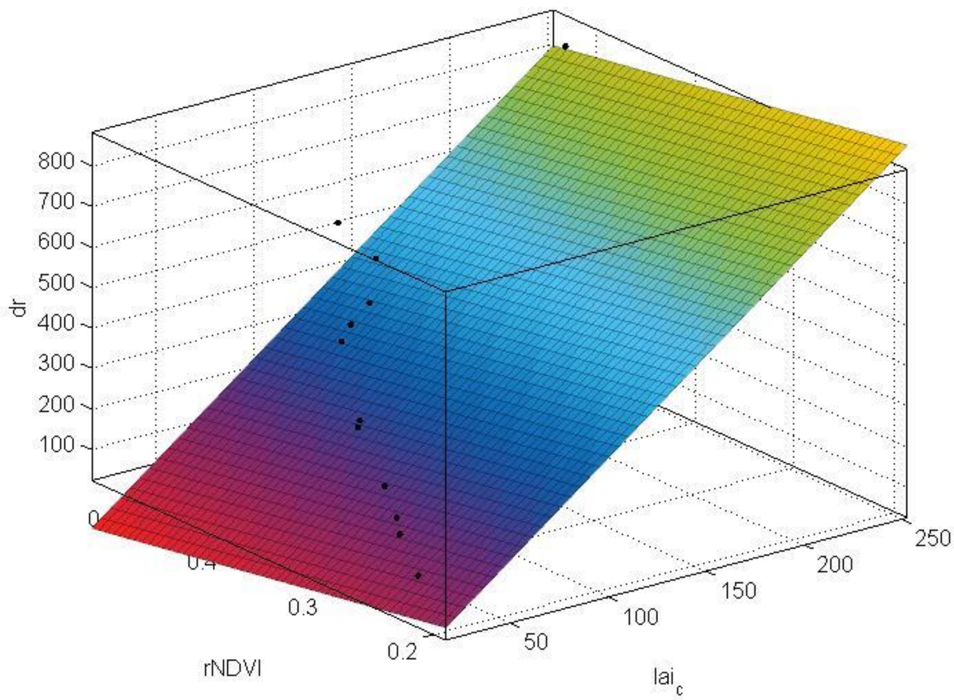


3) Linear model Polynomial (Degree 1, 1), multi variables:

DR_W (LAI_cab, reNDVI) = p00 + p10*LAI_cab + p01*rNDVI [3],

where p00 = 67.6, p10 = 3.776, p01 = -417.5

Goodness of fit: R^2: 0.7095, Adjusted R^2: 0.6862, RMSE: 102



We applied these models to calculate spatial distributions of dry biomass based on remote sensing information (LAI_cab from Sentinel-2).

Models of the dry biomass were used to classify the land covers (grassland and pasture areas). Classification of the modelled dry weight biomass was done by the distribution of the percentage of values. The mean values of data was accepted as 50%. Other percentages (10%, 90%, 100%) were revised from 50%. We assumed that,

- 90-100% vegetation cover shows good growing conditions and this class was defined as grassland with high biomass.
- 50-90% vegetation covers shows poor growing conditions and this class was defined as grassland with poor biomass.
- 10-50% vegetation cover class was defined as open vegetation type.
- 0-10% vegetation cover was defined as rock and scree.

Results

Accuracy assessment was done by using modelled data (DR_W_{mod}) and data from the field trip (DR_W_{obs}):

$$Accuracy=(DR\_W_{obs} – DR\_W_{mod})/ DR\_W_{obs}$$

Accuracy is the probability (%) of a reference (observed) pixel being correctly modelled.

Linear model Models and *R^2 (+names of files)	Goodness of fit between modelled and observed data (Mean Square Error)	Accuracy (%)	Standard deviation of model	Standard deviation of observed data
Polynomial 2 [2] 0.7204 (Polinom2DR1.tif DR_Polin2_Reg.jpg)	0.95	18.7829	1.5403	1.8217
Polynomial 1 [1] 0.7002 (Polinom1DR.tif DR_Polin1_Reg.jpg)	1.0113	16.3857	1.5193	1.8217
Multi variables polynomial 1,1 [3] 0.7095				

**A high R2 value does not guarantee that the model fits the data well*

Recommendations

It is a necessary to improve samples distribution and their numbers for each class to make a better the biomass estimation. Lillesand and Kiefer suggested 50 samples for each land-cover class as rule of thumb.

The sample size (N) can be estimated based on binomial probability theory:

$$N=z^2(p)(q)/E^2 \text{ [5]},$$

Where **p** is the expected percent accuracy of the entire map, **q=p-100**, **E** is the allowable error, and **z**=2(sigma) covering 95.4% of image. Example, if expected accuracy is 85% at an allowable error of 5%, the number of points for a reliable result is 203.

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