National and field scale soil property mapping to support sustainable soil management in Azerbaijan

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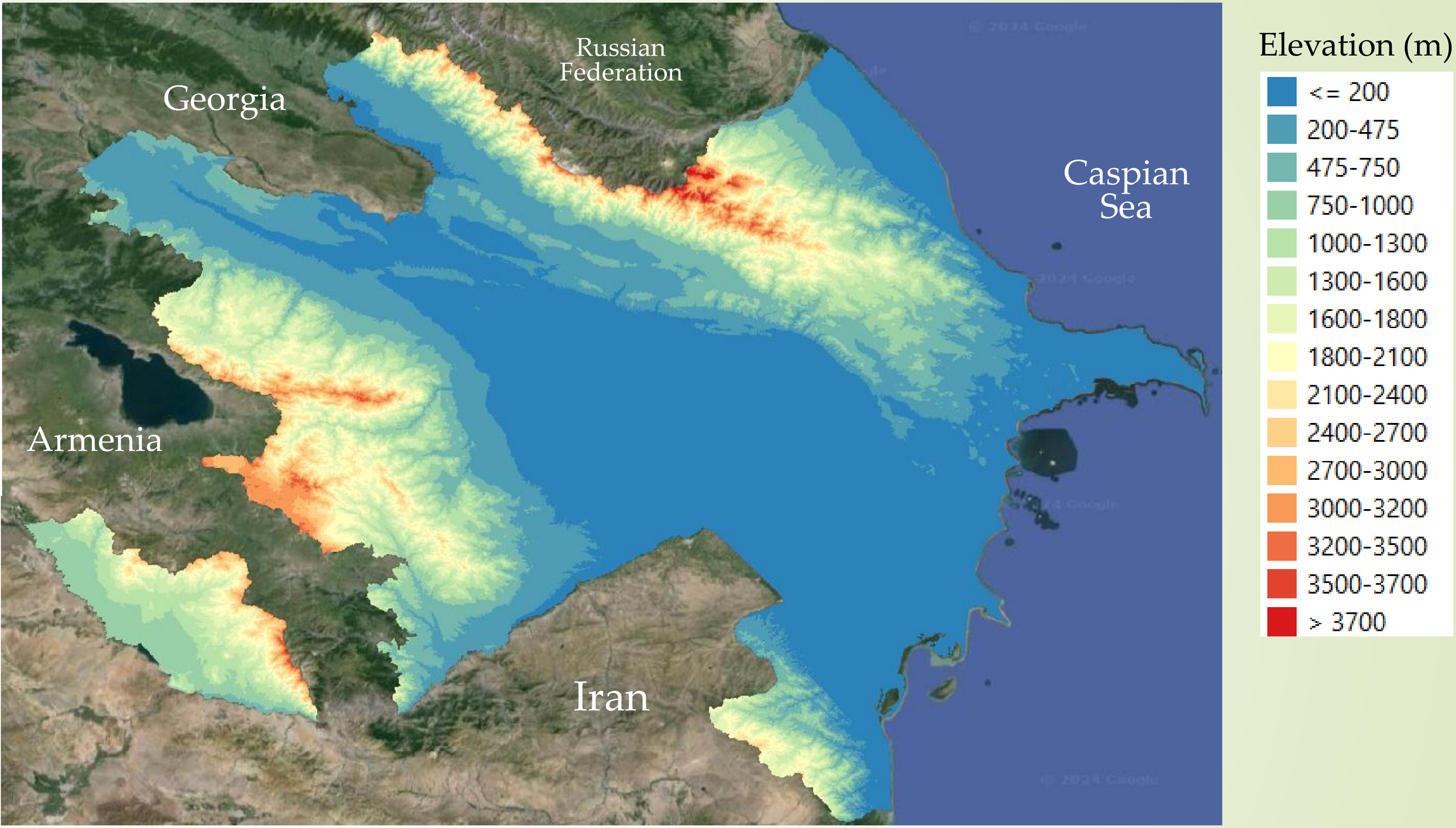
CONTENTS

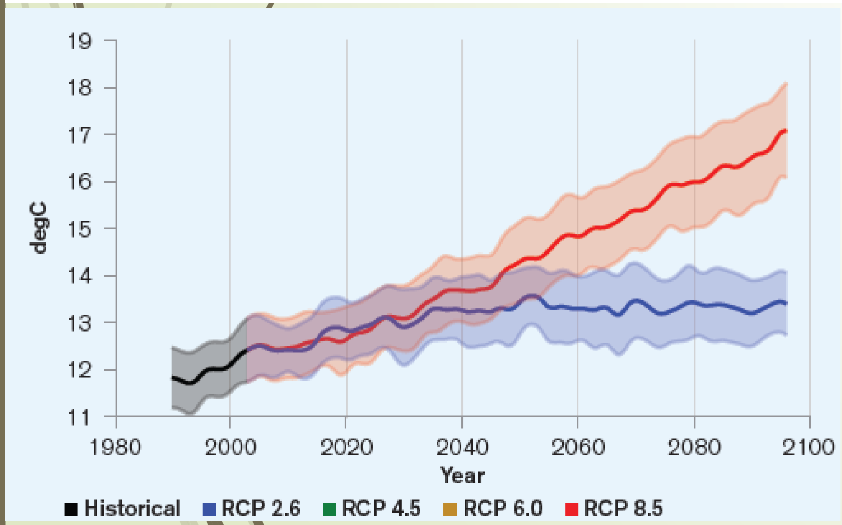
- Soil Resources of Azerbaijan
- National scale soil property mapping
- Field scale soil property mapping
- Soil spectroscopy as a tool supporting digital soil mapping

Soil Resources of Azerbaijan

	Land use structure	**Area (million hectares)**
1	Total land areas	8.66
2	Agricultural lands	4.78
3	Irrigated lands	1.43
4	Salt affected lands	1.25
5	Eroded lands	3.74

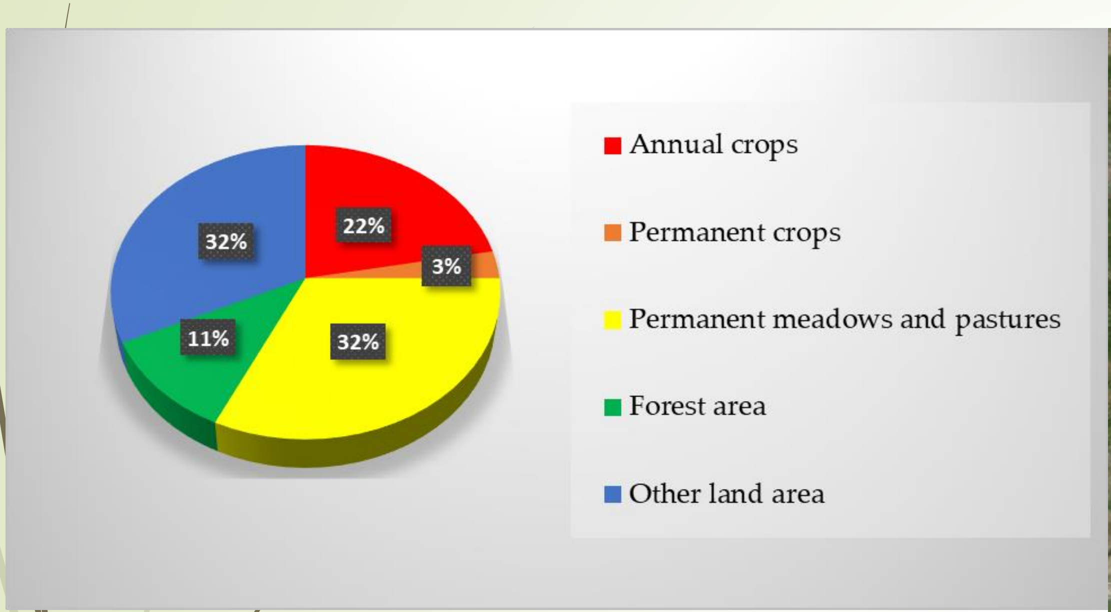


Historic and projected average annual temperature in Azerbaijan under different model ensembles

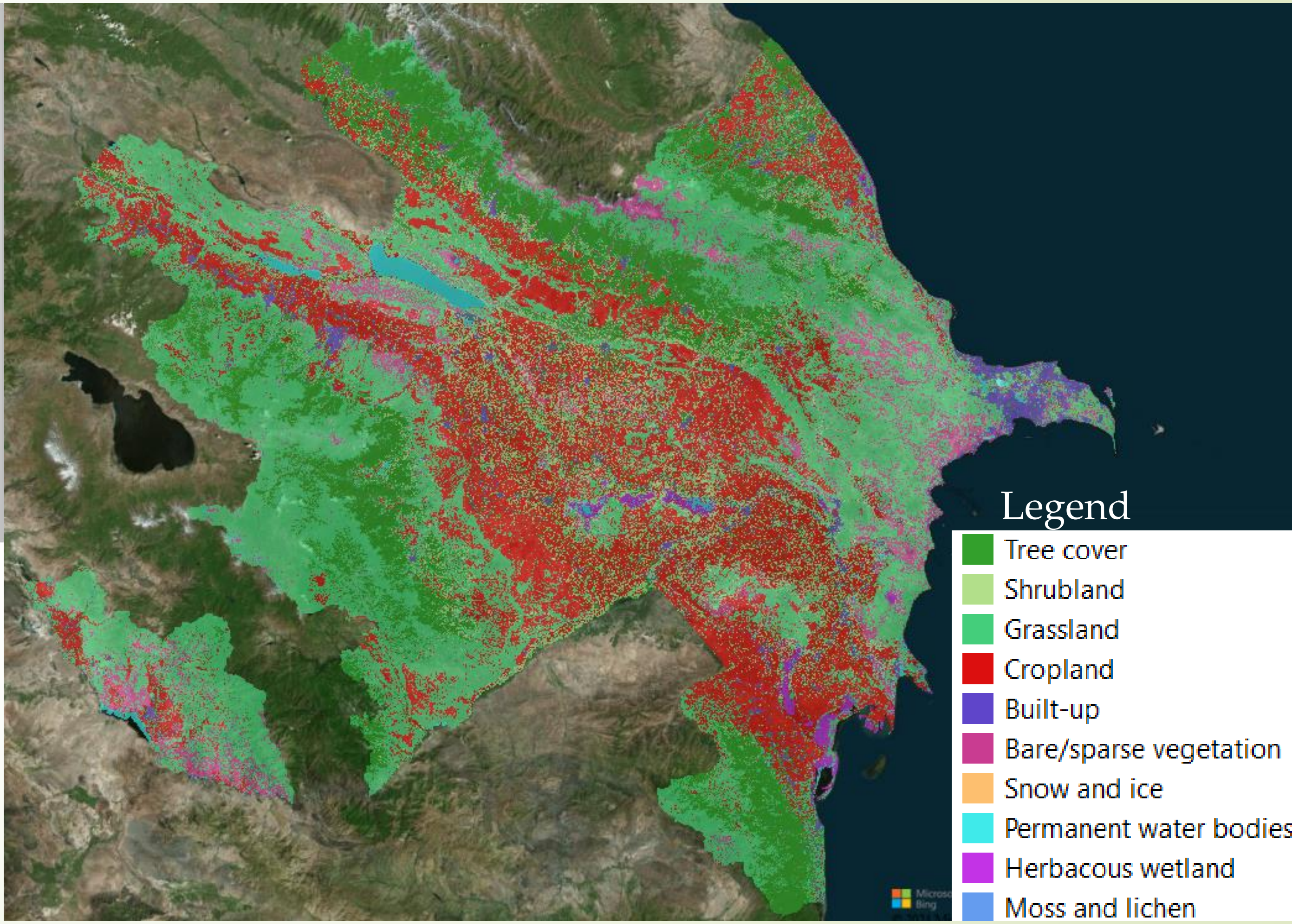


A temperature rise at a faster rate than the global average, by 4.7^{0}C by the 2090s over the 1986–2005 baseline.

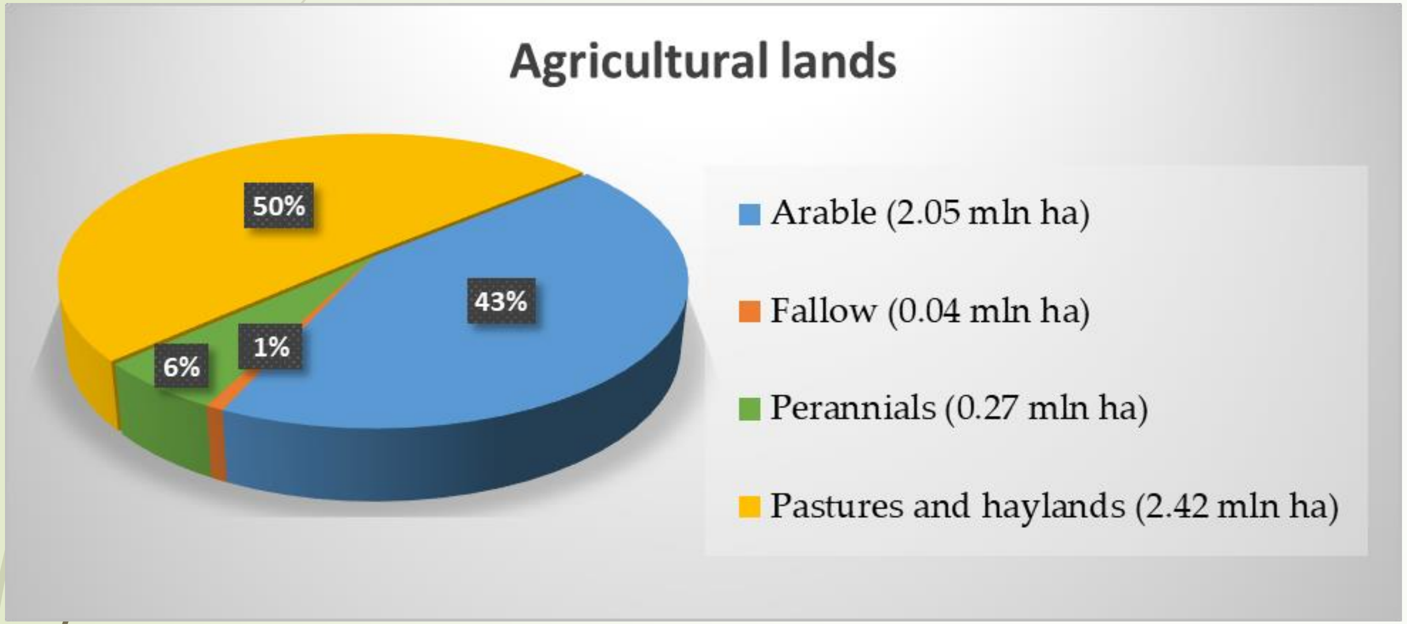
Land use in Azerbaijan

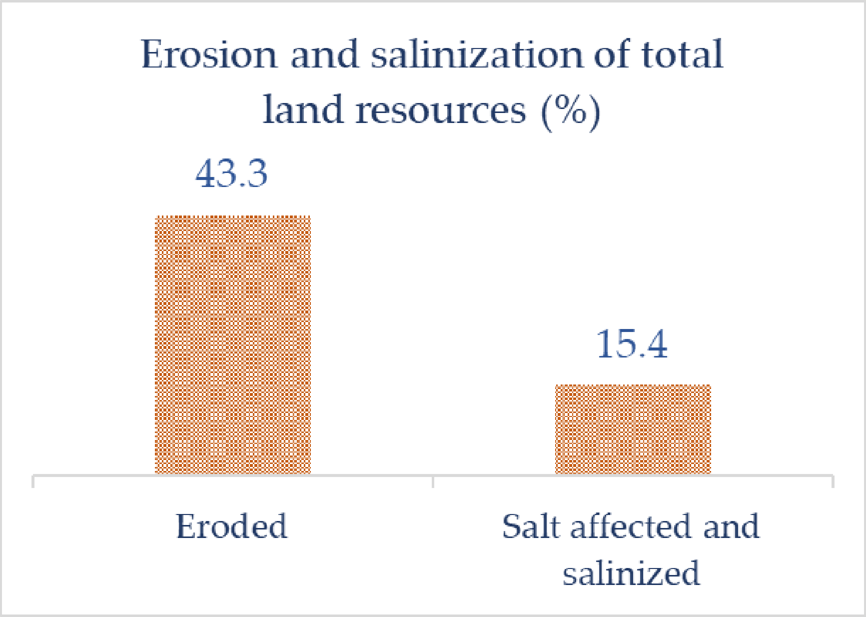


Land Cover Map
Source: ESA World Cover 10m



Agricultural lands in Azerbaijan



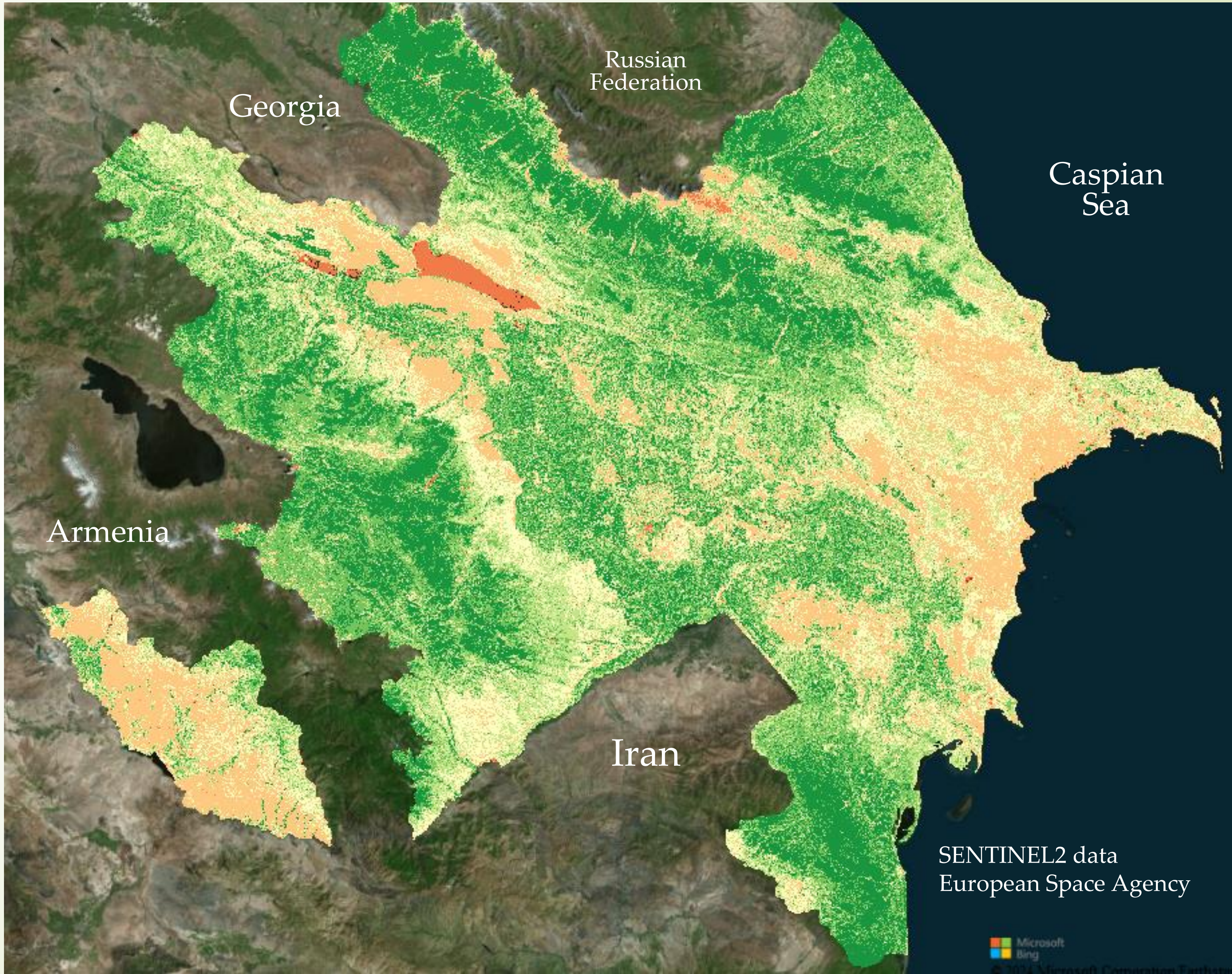


Existing Soil Maps

- Soil Class Map of Azerbaijan (1 : 600 000) – published in 1990s
- Soil Class Map of Azerbaijan (1 : 500 000) – published in Soviet time, 1970s
- State Soil Map of Azerbaijan (1 : 100 000, in total of 83 map sheets) – compiled 1980s
- Old soil maps of collective farms from Soviet union (authorized by local authorities)

Large land areas are bare or characterized with sparse vegetation which highly requires emphasis for sustainable soil management.

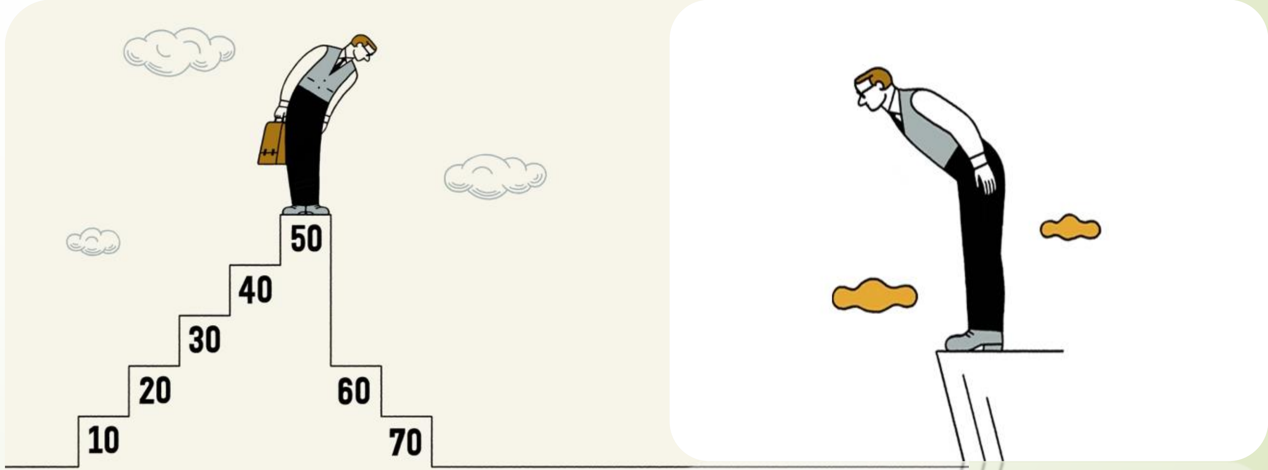
Maximum NDVI values observed in 2022



SENTINEL2 data
European Space Agency

National scale soil property mapping in Azerbaijan

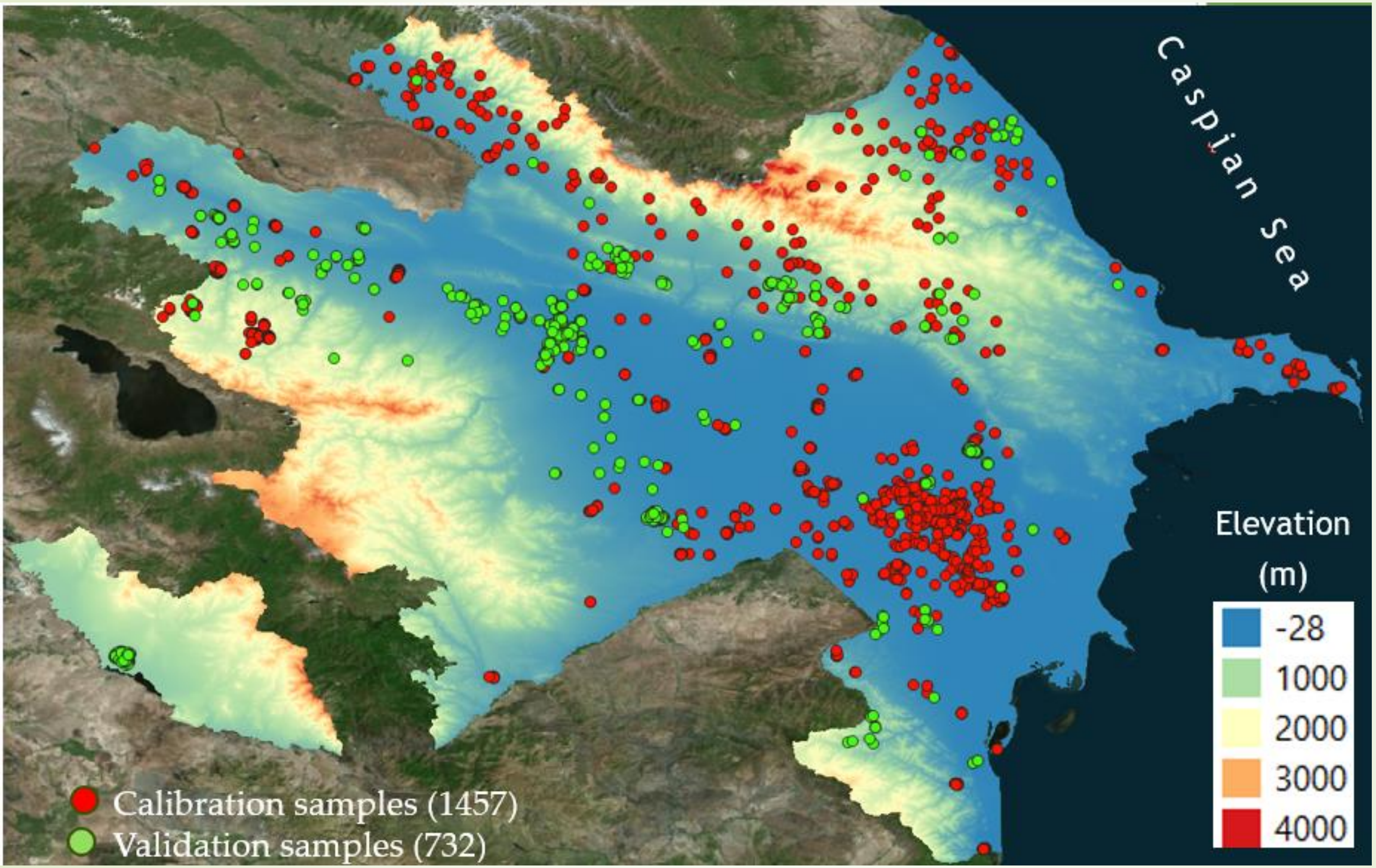
We are in pioneering phase in digital soil mapping because of unavailability of up-to-dated or legacy soil data.



FULBRIGHT Scholar Program

WISCONSIN UNIVERSITY OF WISCONSIN-MADISON

National scale soil pH mapping using legacy data in Azerbaijan

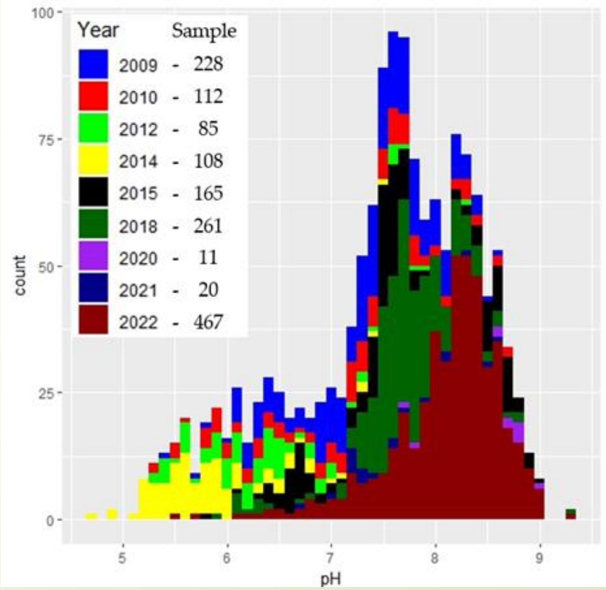


- Supervised by:

Prof. V.Radeloff

Prof. A.Hartemink

Prof. M.Ozdogan



List of predictor data

DEM	SENTINEL 2 (2019-2022)	WorldClim variables	Land Form/ Land Cover/ Land Use	Sediment
SRTM 30 **SRTM 90** **TanDEM 90** **ALOS PALSAR 30** **DEM derivatives**: *El – Elevation * 4* *SL – Slope * 3* *AS – Aspect (cos) * 3* *C – Curvature * 1* *PrC – Profile curvature * 1* *PlC – Plan curvature * 1* *Hl – Hillshade * 3* *TWI – Wetness index * 4* *LS – LS factor * 1*	NDVI - (max and median) * 8 EVI - (max and median) * 8 TNDVI - (max and median) * 8 WDVI - (max and median) * 8 GCI - (max and median) * 8 DI *1 NDI *1 NSI *1 RI *1 TBI *1 TGSI *1 Bands *9	Bio01 Bio02 Bio03 Bio04 Bio05 Bio06 Bio07 Bio08 Bio09 Bio10 Bio11 Bio12 Bio13 Bio14 Bio15 Bio16 Bio17 Bio18 Bio19 Solar radiation Wind velocity	Global ALOS Landform * 1 Global ALOS Topographic Diversity * 1 Global ALOS mTPI * 1 ESA World Cover * 1 Land use from ground * 1 (forest, shrubland, pasture, hayfield, arable, newly arable)	Quaternary Sediment Map of Azerbaijan (M 1:500,000)
21	55	21	5	1
Sum				103

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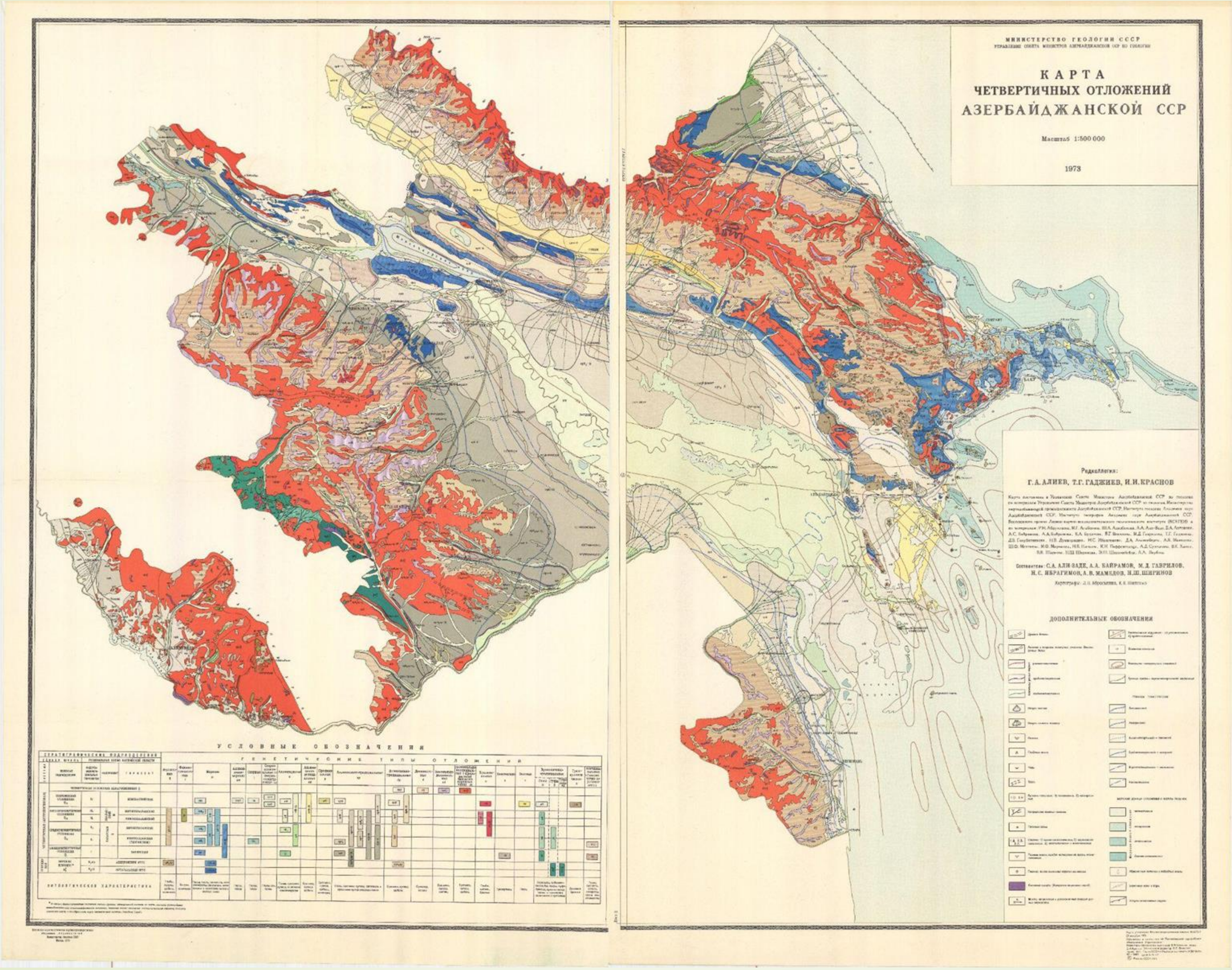
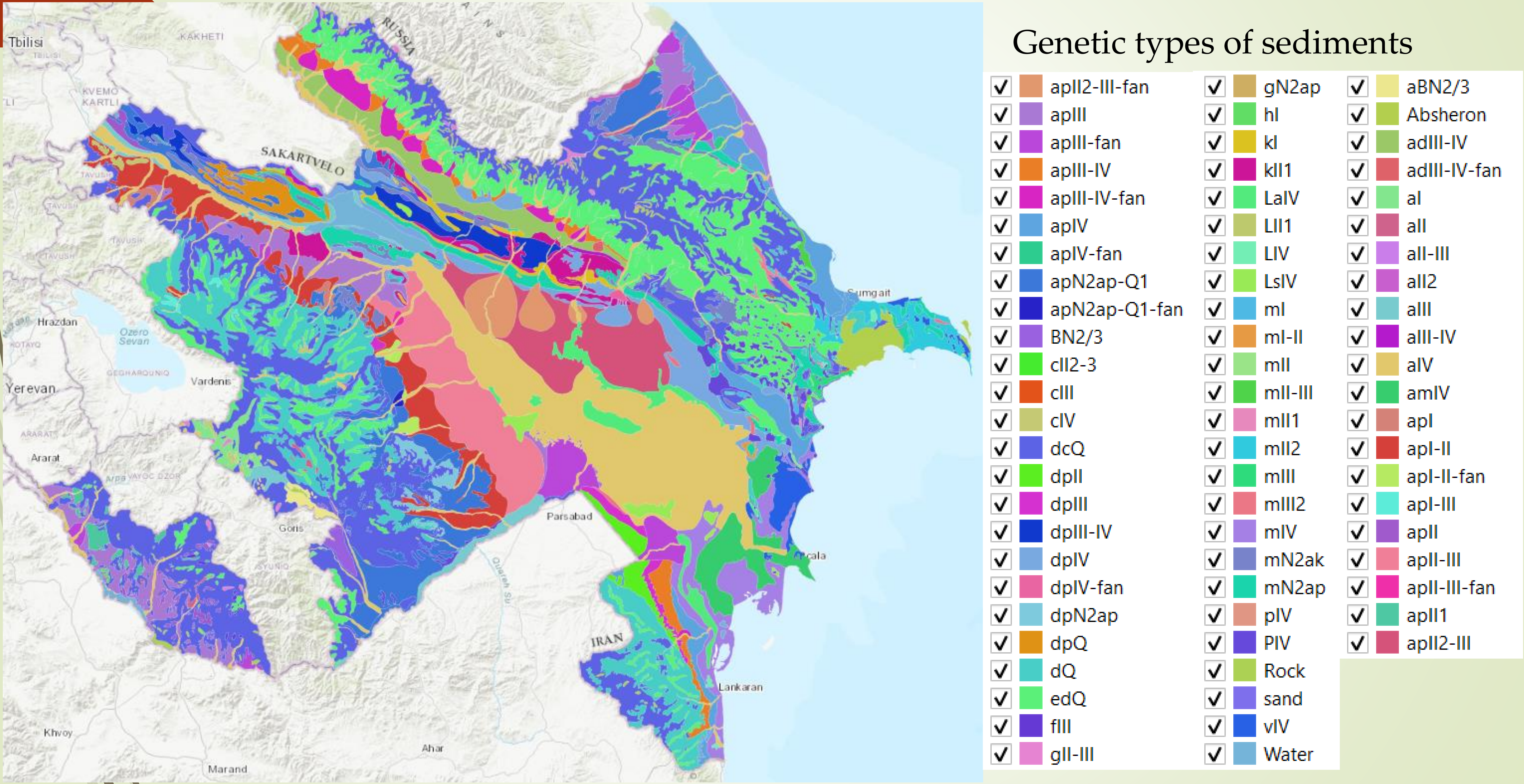
Quaternary sediment map



Quaternary Sediments Map of Azerbaijan



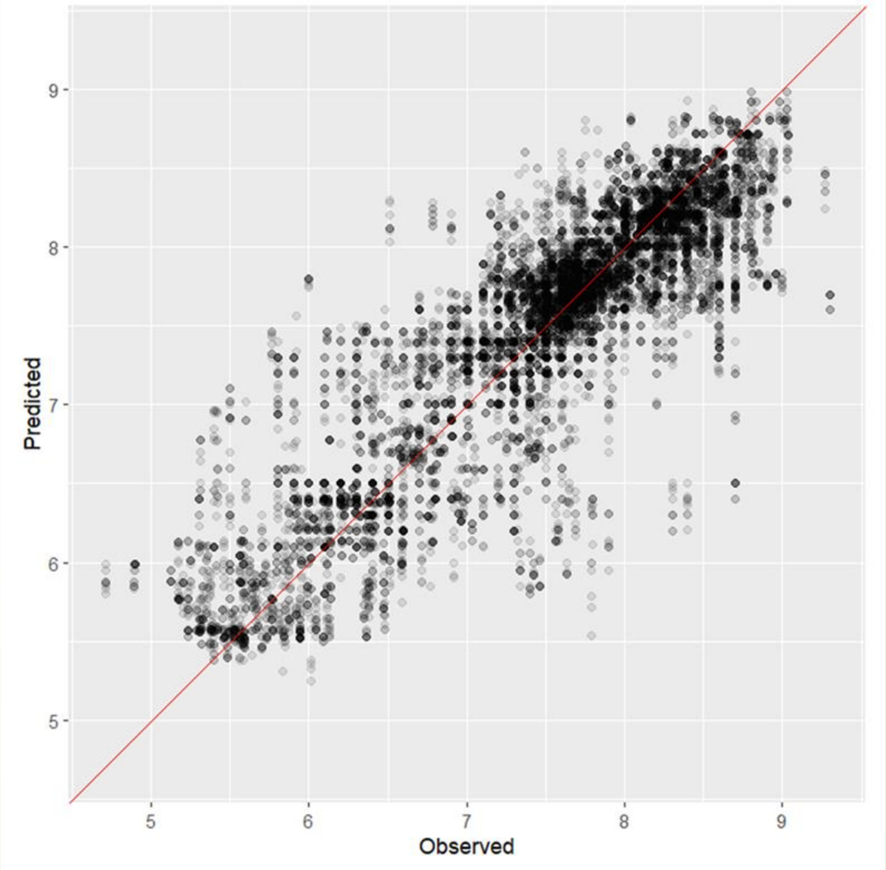
Genetic types of sediments

Model performance

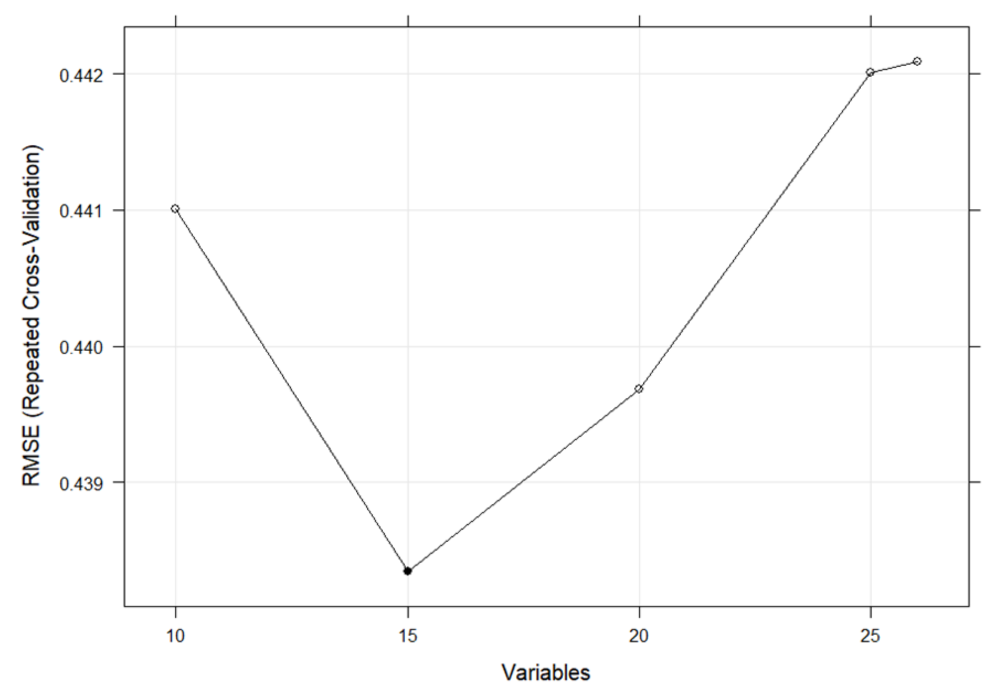
Model	R^2	MSE	RMSE	MAE
Quantile Regression Forest	0.76	0.19	0.44	0.31
Random Forest Regression	0.75	0.21	0.46	0.34
X Boost	0.71	0.23	0.48	0.36
Cubist	0.70	0.25	0.50	0.37
Multiple Linear Regression	0.66	0.27	0.52	0.42
Support Vector Regression	0.66	0.28	0.53	0.40
Decision Trees	0.65	0.29	0.54	0.43

R^2 – coefficient of determination
MSE – mean squared error
RMSE – root mean squared error
MAE – mean absolute error

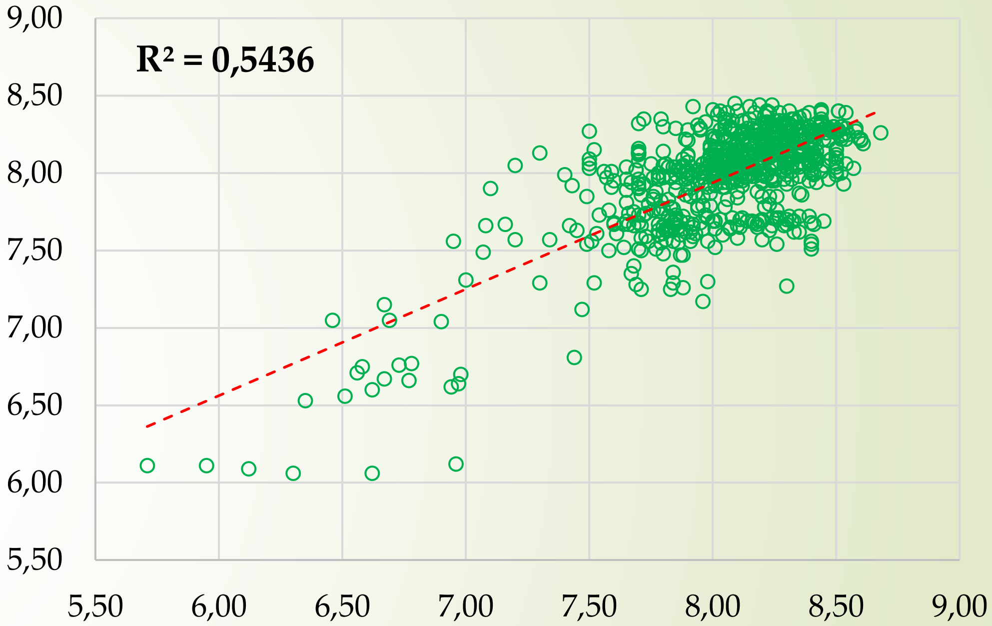
10-fold cross-validation



Recursive Feature Elimination

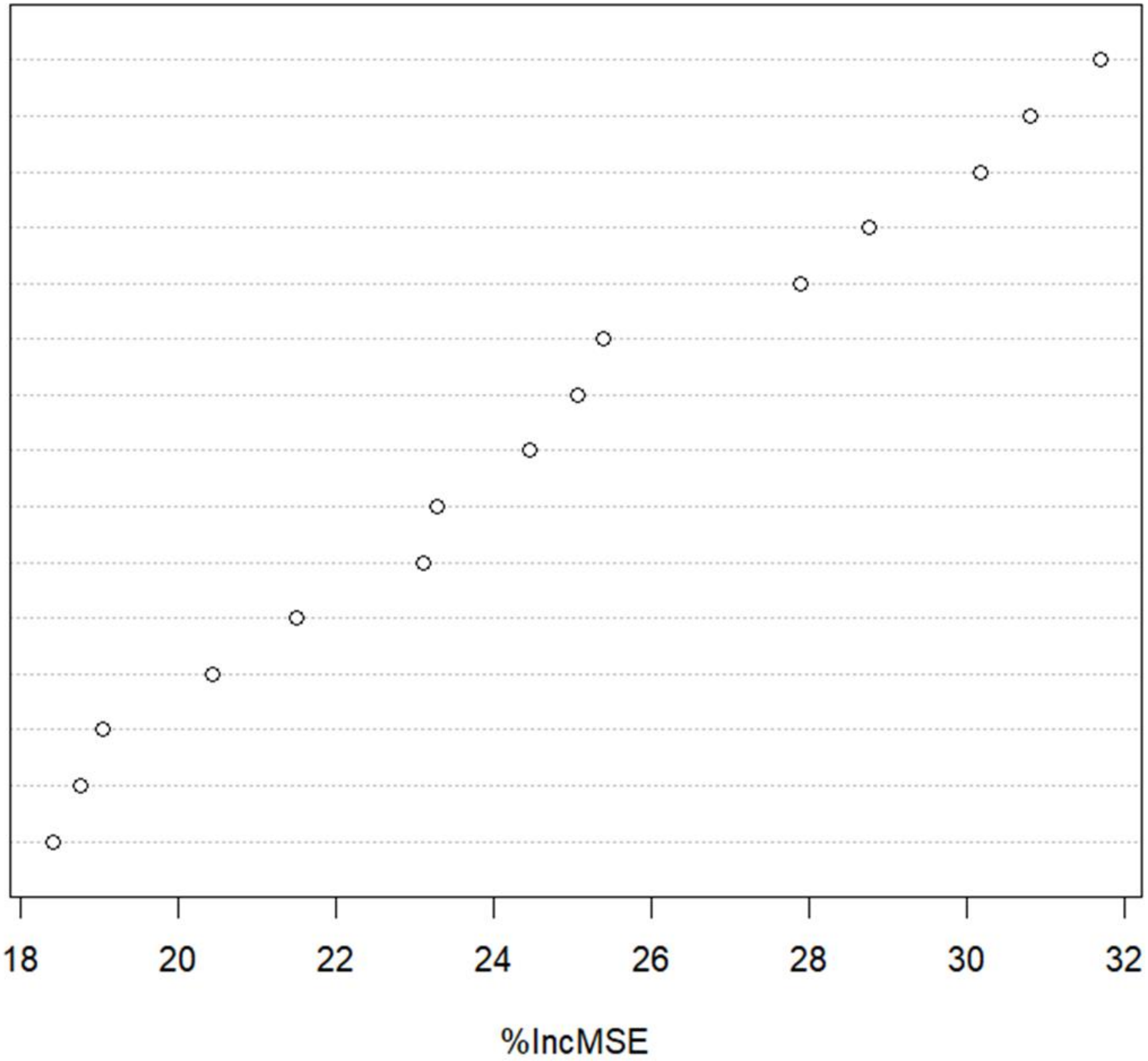


Model validation

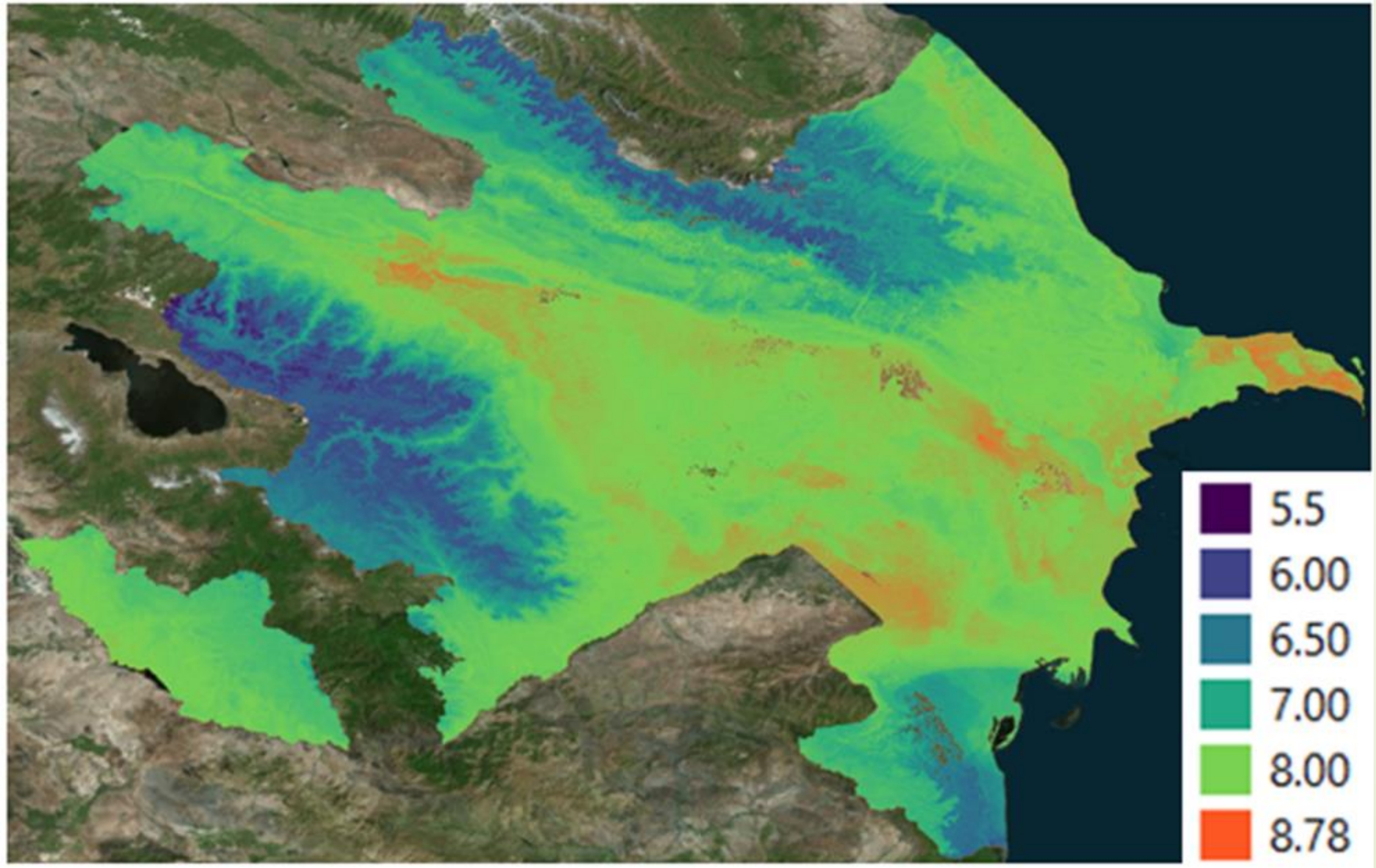


Variable importance for QRF

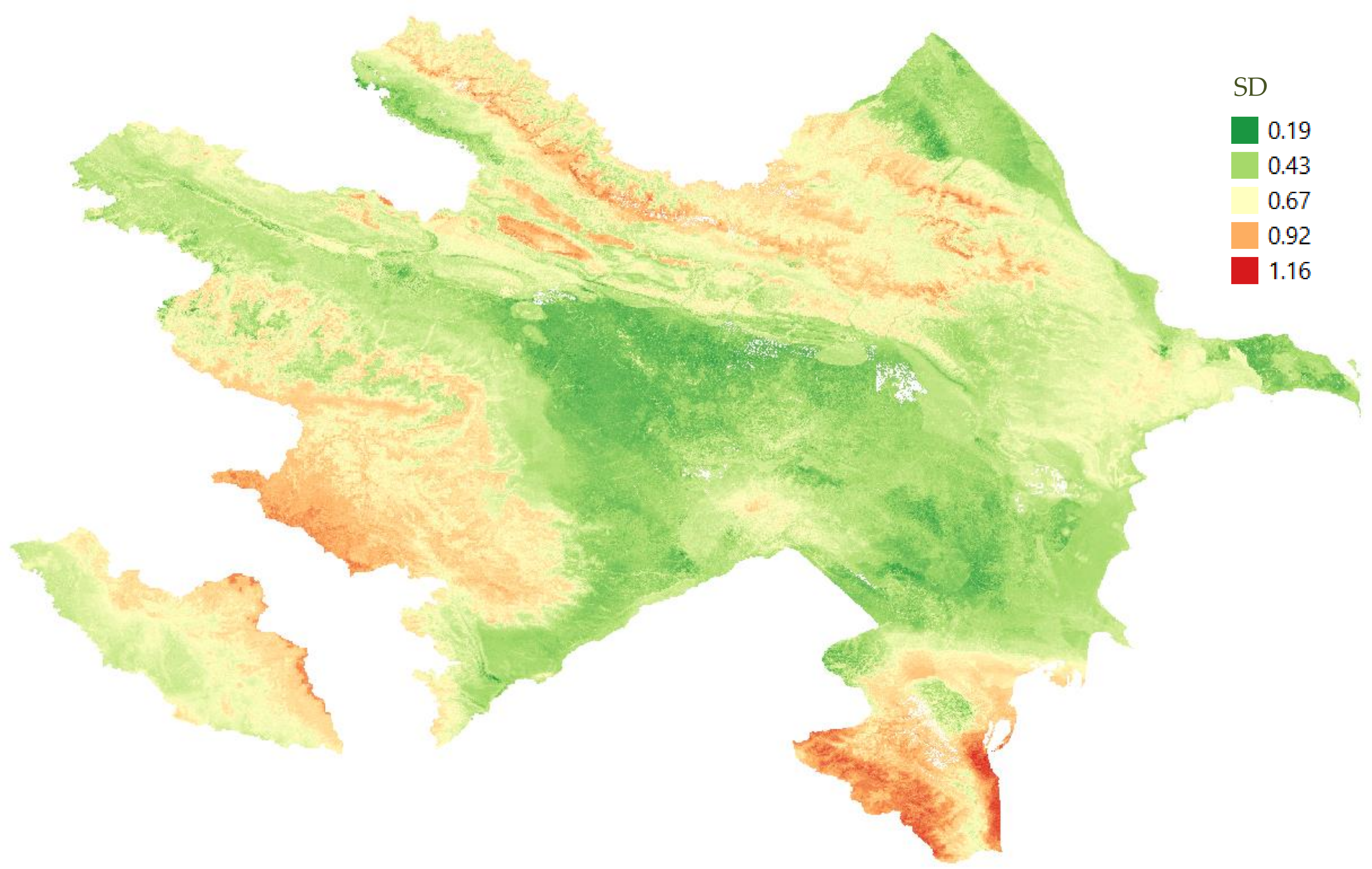
medianNDVI2021------------------------NDVI
medianGCI2021----------------------------GCI
Precipitation coldest quarter-----------Bio19
Average wind velocity-----------------Wind
Solar radiation----------------------------Solar
Sediment------------------------------Sediment
Topographic Diver. Index-----------TDI
Slope---------------------------------TanDEM90
Elevation ------------------------------SRTM90
Precipitation wettest month-----------Bio13
Temperature seasonality--------------Bio04
Precipitation warmest quarter--------Bio18
Annual precipitation-------------------Bio12
Precipitation of wettest quarter------Bio16
Mean diurnal range--------------------Bio02



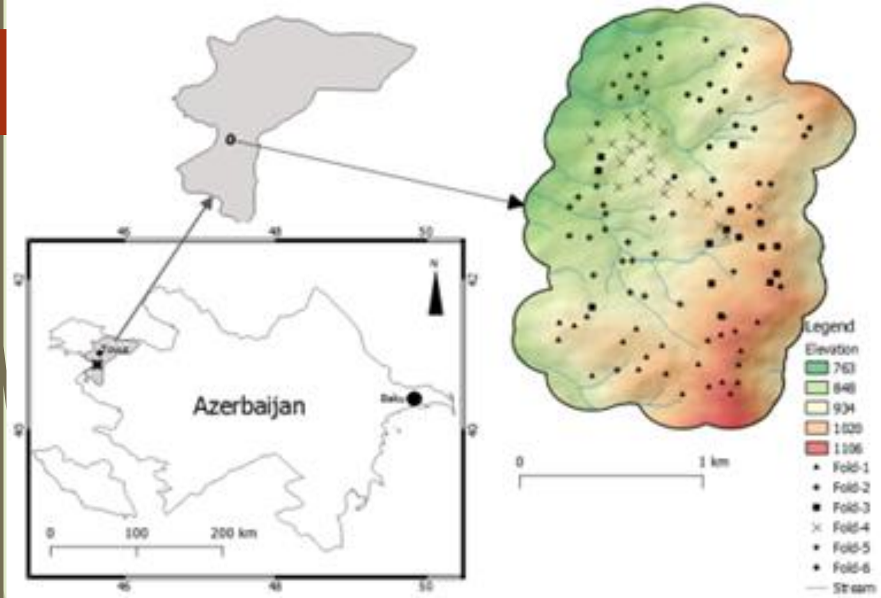
Predicted pH map with Quantile Regression Forest



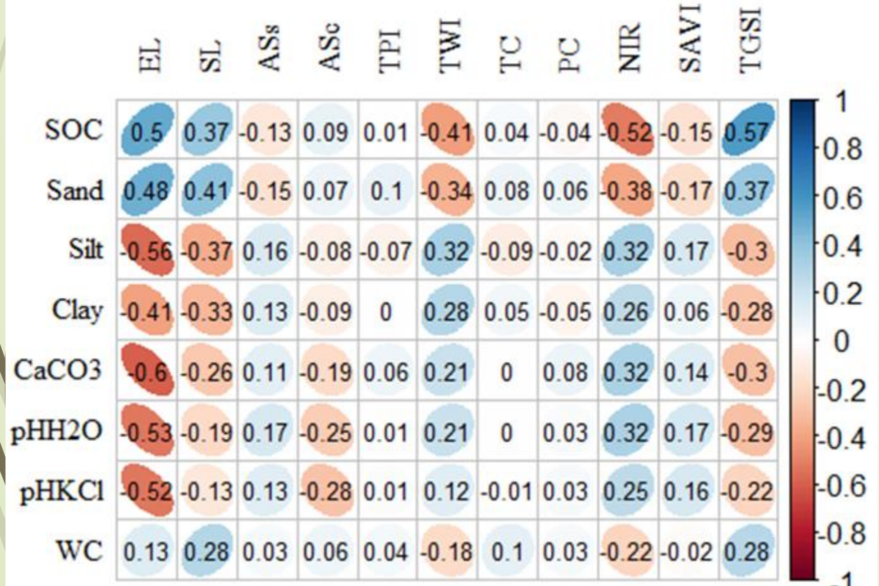
Uncertainty of Quantile Regression Forest Model



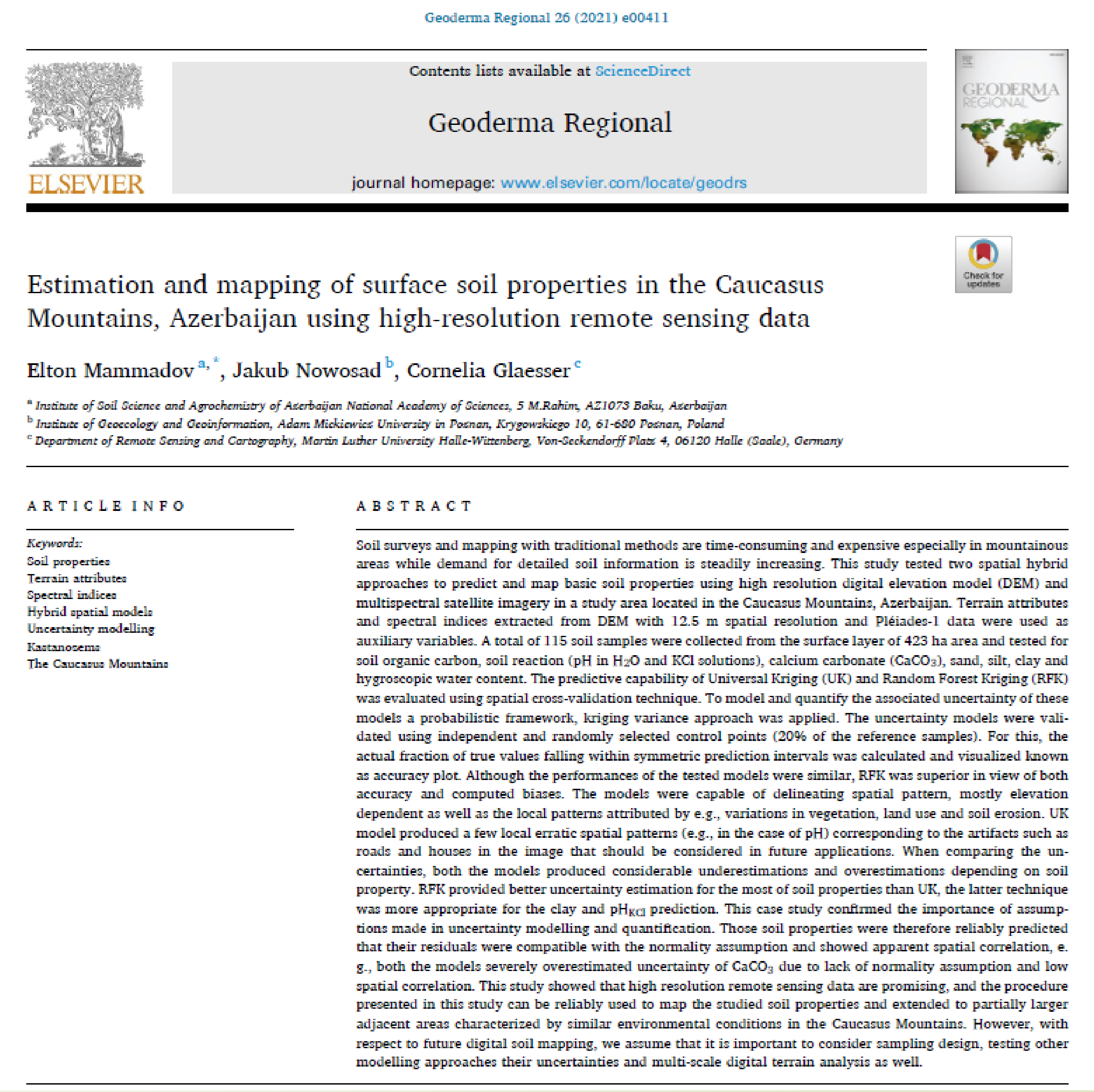
Field scale soil property mapping in Azerbaijan



Spearman's Rho correlation coefficients between tested soil properties and auxiliary variables



	EL	SL	ASs	ASc	TPI	TWI	TC	PC	NIR	SAVI	TGSI
SOC	0.5	0.37	-0.13	0.09	0.01	-0.41	0.04	-0.04	-0.52	-0.15	0.57
Sand	0.48	0.41	-0.15	0.07	0.1	-0.34	0.08	0.06	-0.38	-0.17	0.37
Silt	-0.56	-0.37	0.16	-0.08	-0.07	0.32	-0.09	-0.02	0.32	0.17	-0.3
Clay	-0.41	-0.33	0.13	-0.09	0	0.28	0.05	-0.05	0.26	0.06	-0.28
CaCO3	-0.6	-0.26	0.11	-0.19	0.06	0.21	0	0.08	0.32	0.14	-0.3
pHH2O	-0.53	-0.19	0.17	-0.25	0.01	0.21	0	0.03	0.32	0.17	-0.29
pHKCl	-0.52	-0.13	0.13	-0.28	0.01	0.12	-0.01	0.03	0.25	0.16	-0.22
WC	0.13	0.28	0.03	0.06	0.04	-0.18	0.1	0.03	-0.22	-0.02	0.28



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Estimation and mapping of surface soil properties in the Caucasus Mountains, Azerbaijan using high-resolution remote sensing data

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[b] *Institute of Geoecology and Geoinformation, Adam Mickiewicz University in Poznan, Krygowskiego 10, 61-680 Poznan, Poland*
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Uncertainty modelling
Kastanozems
The Caucasus Mountains

ABSTRACT

Soil surveys and mapping with traditional methods are time-consuming and expensive especially in mountainous areas while demand for detailed soil information is steadily increasing. This study tested two spatial hybrid approaches to predict and map basic soil properties using high resolution digital elevation model (DEM) and multispectral satellite imagery in a study area located in the Caucasus Mountains, Azerbaijan. Terrain attributes and spectral indices extracted from DEM with 12.5 m spatial resolution and Pléiades-1 data were used as auxiliary variables. A total of 115 soil samples were collected from the surface layer of 423 ha area and tested for soil organic carbon, soil reaction (pH in H_2O and KCl solutions), calcium carbonate ($CaCO_3$), sand, silt, clay and hygroscopic water content. The predictive capability of Universal Kriging (UK) and Random Forest Kriging (RFK) was evaluated using spatial cross-validation technique. To model and quantify the associated uncertainty of these models a probabilistic framework, kriging variance approach was applied. The uncertainty models were validated using independent and randomly selected control points (20% of the reference samples). For this, the actual fraction of true values falling within symmetric prediction intervals was calculated and visualized known as accuracy plot. Although the performances of the tested models were similar, RFK was superior in view of both accuracy and computed biases. The models were capable of delineating spatial pattern, mostly elevation dependent as well as the local patterns attributed by e.g., variations in vegetation, land use and soil erosion. UK model produced a few local erratic spatial patterns (e.g., in the case of pH) corresponding to the artifacts such as roads and houses in the image that should be considered in future applications. When comparing the uncertainties, both the models produced considerable underestimations and overestimations depending on soil property. RFK provided better uncertainty estimation for the most of soil properties than UK, the latter technique was more appropriate for the clay and pH_{KCl} prediction. This case study confirmed the importance of assumptions made in uncertainty modelling and quantification. Those soil properties were therefore reliably predicted that their residuals were compatible with the normality assumption and showed apparent spatial correlation, e.g., both the models severely overestimated uncertainty of $CaCO_3$ due to lack of normality assumption and low spatial correlation. This study showed that high resolution remote sensing data are promising, and the procedure presented in this study can be reliably used to map the studied soil properties and extended to partially larger adjacent areas characterized by similar environmental conditions in the Caucasus Mountains. However, with respect to future digital soil mapping, we assume that it is important to consider sampling design, testing other modelling approaches their uncertainties and multi-scale digital terrain analysis as well.

Model performance with spatial cross-validation technique

Soil constituent	Model	RMSE	SD_{RMSE}	ME	SD_{ME}	RPD	SD_{RPD}
SOC	UK RFK	0.94 0.95	0.26 0.27	0.04 − 0.02	0.23 0.35	1.20 1.20	0.22 0.24
Sand	UK RFK	16.0 15.0	4.00 3.50	0.49 − 0.47	10.10 8.10	0.98 1.05	0.13 0.12
Silt	UK RFK	10.0 10.0	1.60 1.30	0.24 0.54	5.80 4.50	1.00 1.00	0.22 0.15
Clay	UK RFK	7.1 6.5	1.80 2.00	− 0.32 − 0.04	4.20 4.00	0.93 1.02	0.15 0.19
$CaCO_3$	UK RFK	2.10 2.00	0.26 0.42	0.18 0.11	1.02 0.79	1.10 1.10	0.28 0.30
pH_{H2O}	UK RFK	0.36 0.38	0.08 0.09	0.06 0.03	0.18 0.18	1.10 1.10	0.34 0.22
pH_{KCl}	UK RFK	0.43 0.45	0.10 0.12	0.08 0.04	0.20 0.20	1.10 1.10	0.36 0.22
WC	UK RFK	1.00 0.95	0.12 0.12	− 0.03 − 0.07	0.46 0.34	0.97 1.04	0.07 0.15

UK - Universal kriging

RFK - Random Forest Kriging

RMSE – Root Mean Squared Error

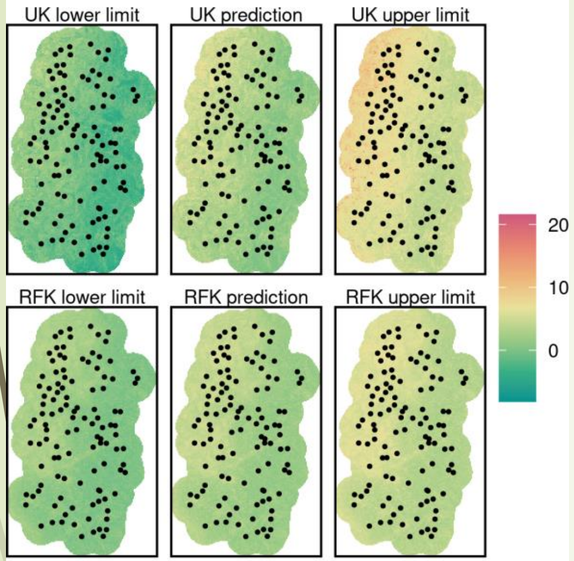
ME – mean error

SD - Standard Deviation

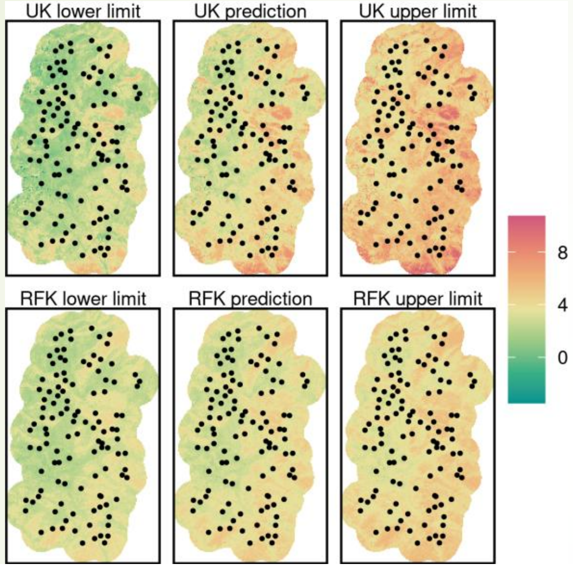
RPD - Residual Prediction Deviation

Predicted maps with Universal Kriging and Random Forest Kriging

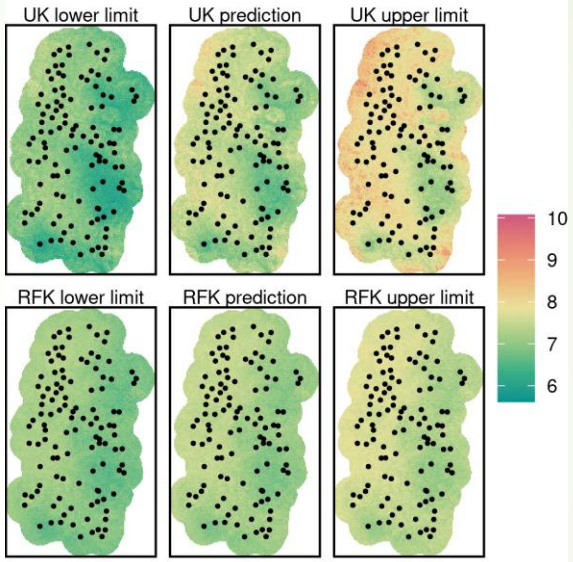
$CaCO_3$ (%)



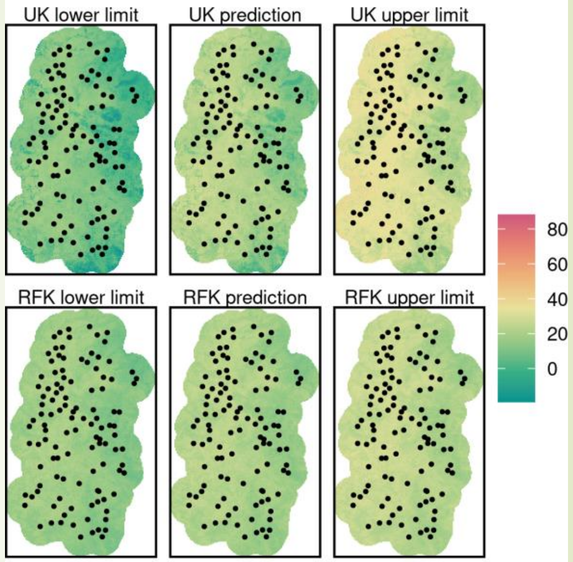
SOC (%)



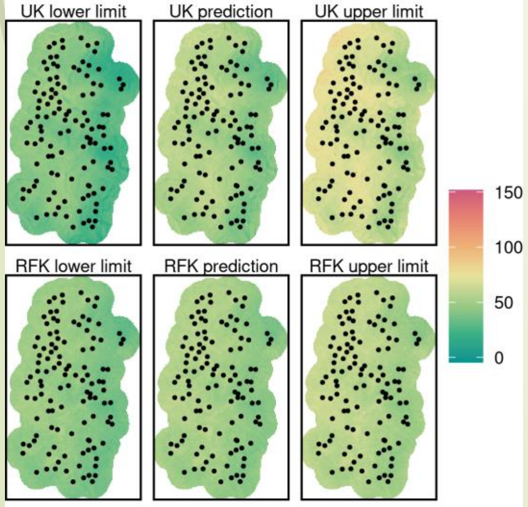
pH



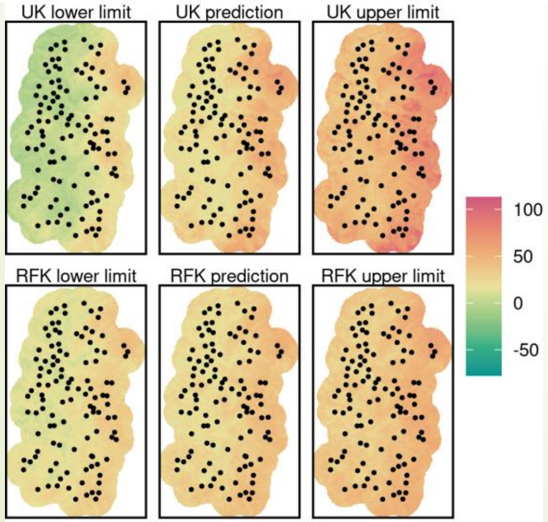
Clay (%)



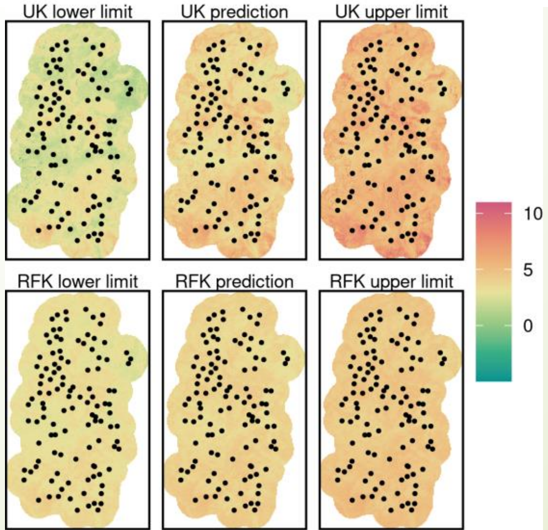
Silt (%)



Sand (%)



WC (%)



Field scale soil mapping in salt affected agricultural land

Total area: 630 ha

Pivot area: 400 ha

Irregular sampling scheme

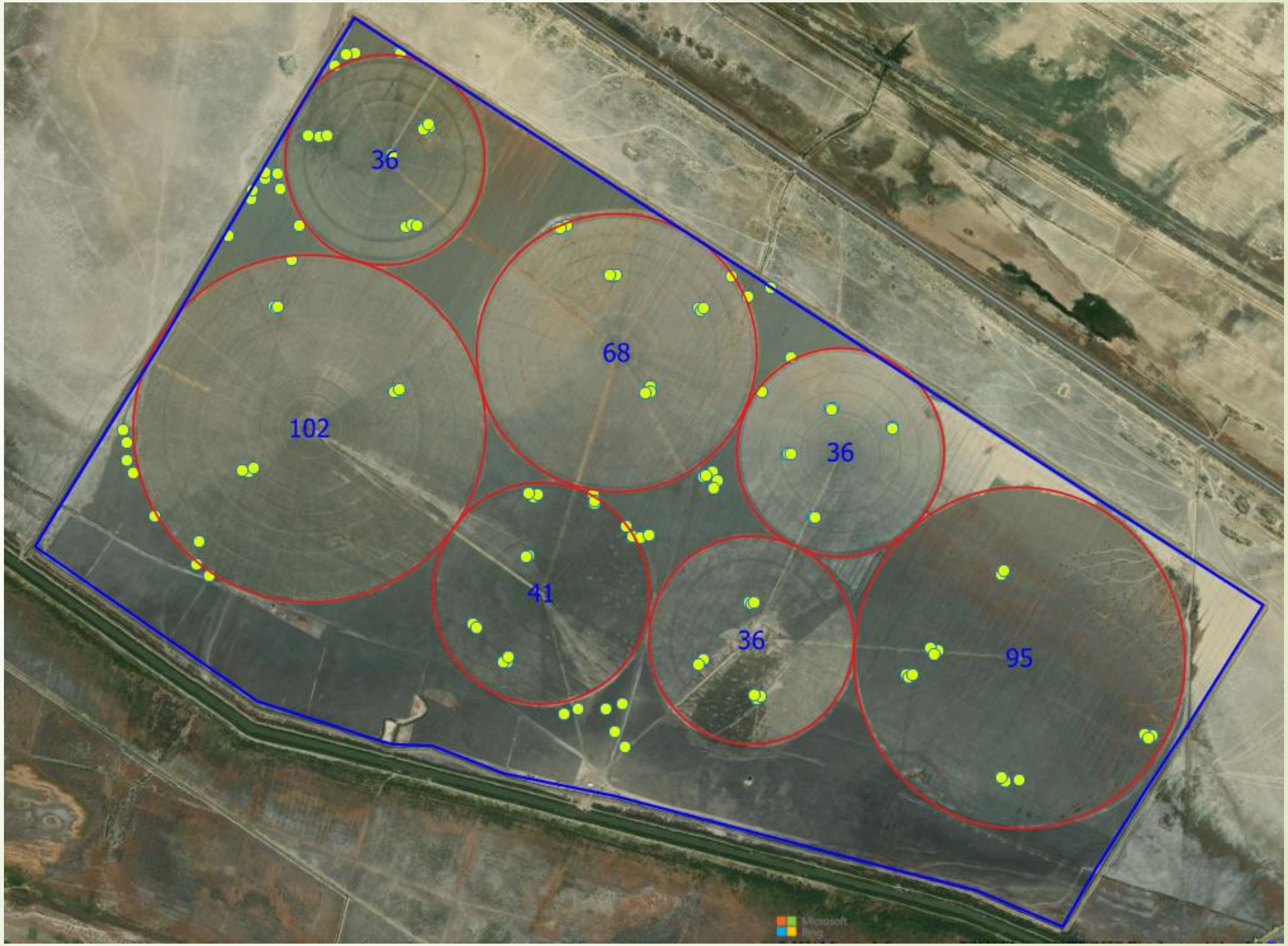
Total soil samples: 124

Pivot: 81

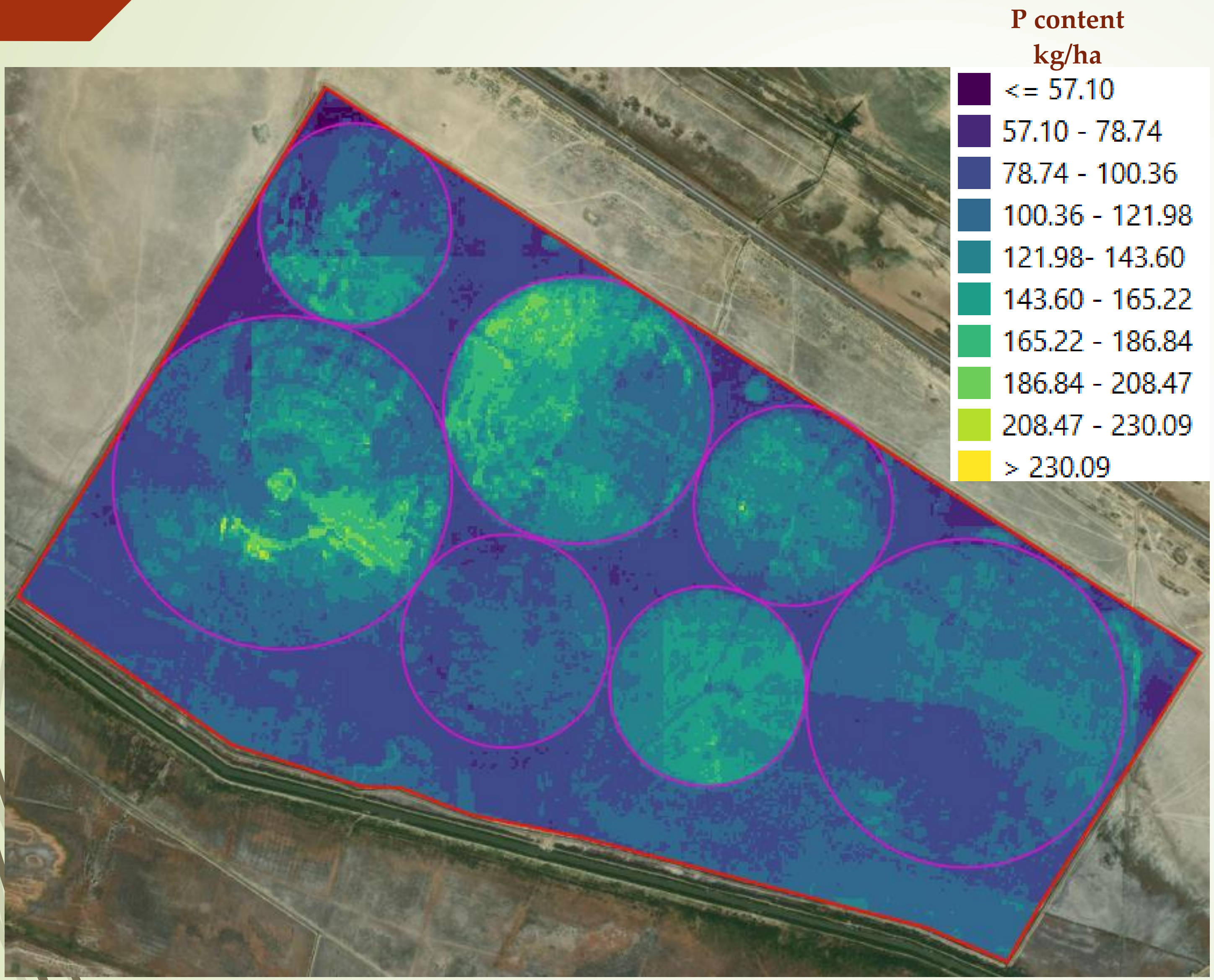
Pivot outside: 43

Tested soil properties

1. SOC
2. $CaCO_3$
3. Saturation
4. pH
5. EC
6. P
7. K



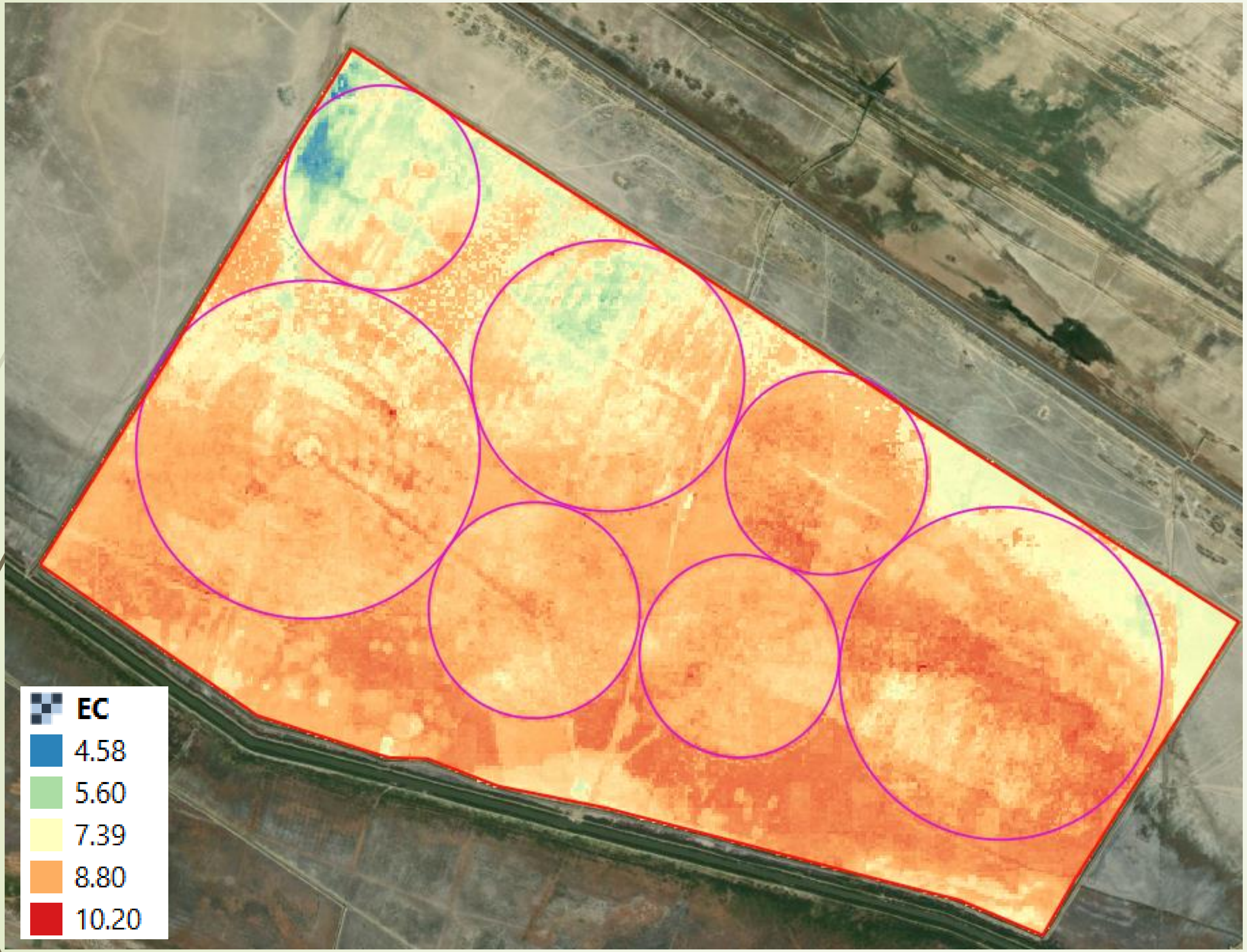
Phosphorus map predicted with QRF



Model performance with 10-fold cross-validation

Soil property	R^2	RMSE
SOC	0.61	0.49
pH	0.32	0.61
EC	0.41	1.25
N	0.39	0.02
P	0.42	22.5
K	0.44	81.0

EC map predicted with QRF



- EC classification

0-4 – non-saline

4-8 – slightly saline

8-12 – moderately saline

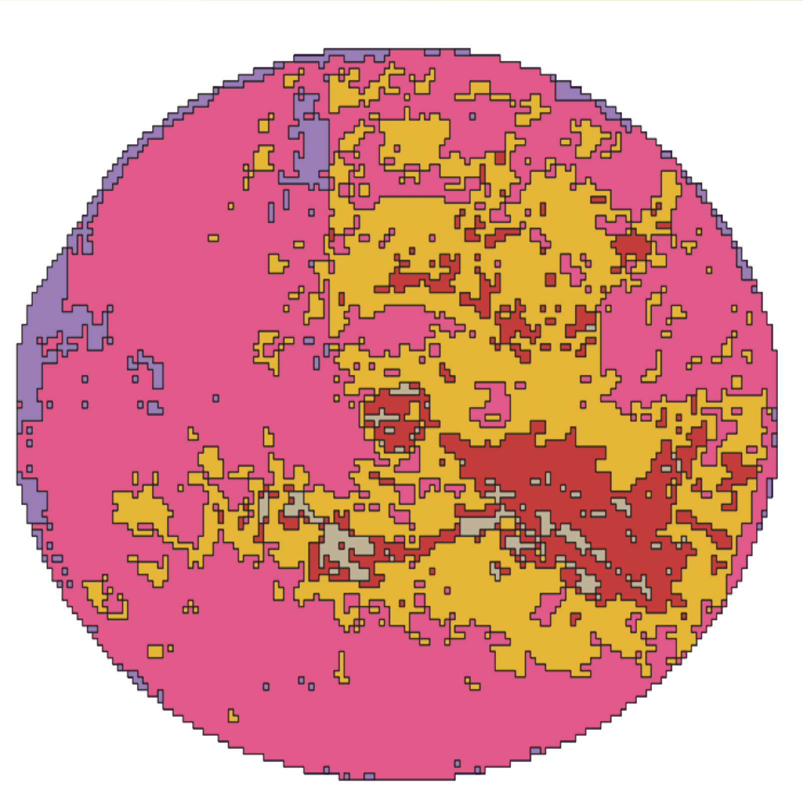
12-16 – strongly saline

>16 – extremely saline

VRT application of P fertilizer

P scale	Area (ha)	P content (kg/ha)	P application with traditional approach (kg/ha)	Precision (VRT)
🟪	4.2	90	135	135
🟥	57.0	107	135	118
🟨	30.0	139	135	86
🟫	9.0	171	135	54
⬛	2.3	187	135	38
Sum	**102.5 ha**		**13770 kq**	**10446 kq**
Saved capital			**3324 kg * 1.6 AZN = 5318 AZN ~ 2921 €**	

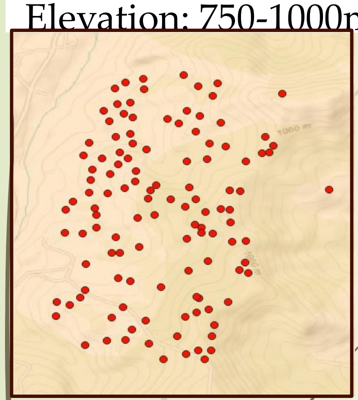
A 102 ha
of pivot



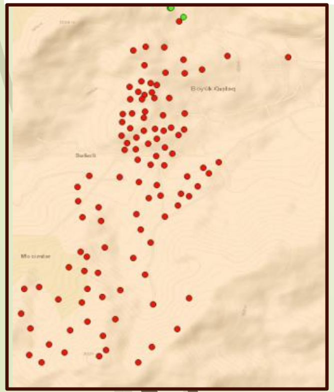
The amount of saved money per hectare in the case of P: 52 AZN ~ 29.2 €

Soil spectroscopy as a tool supporting digital soil mapping

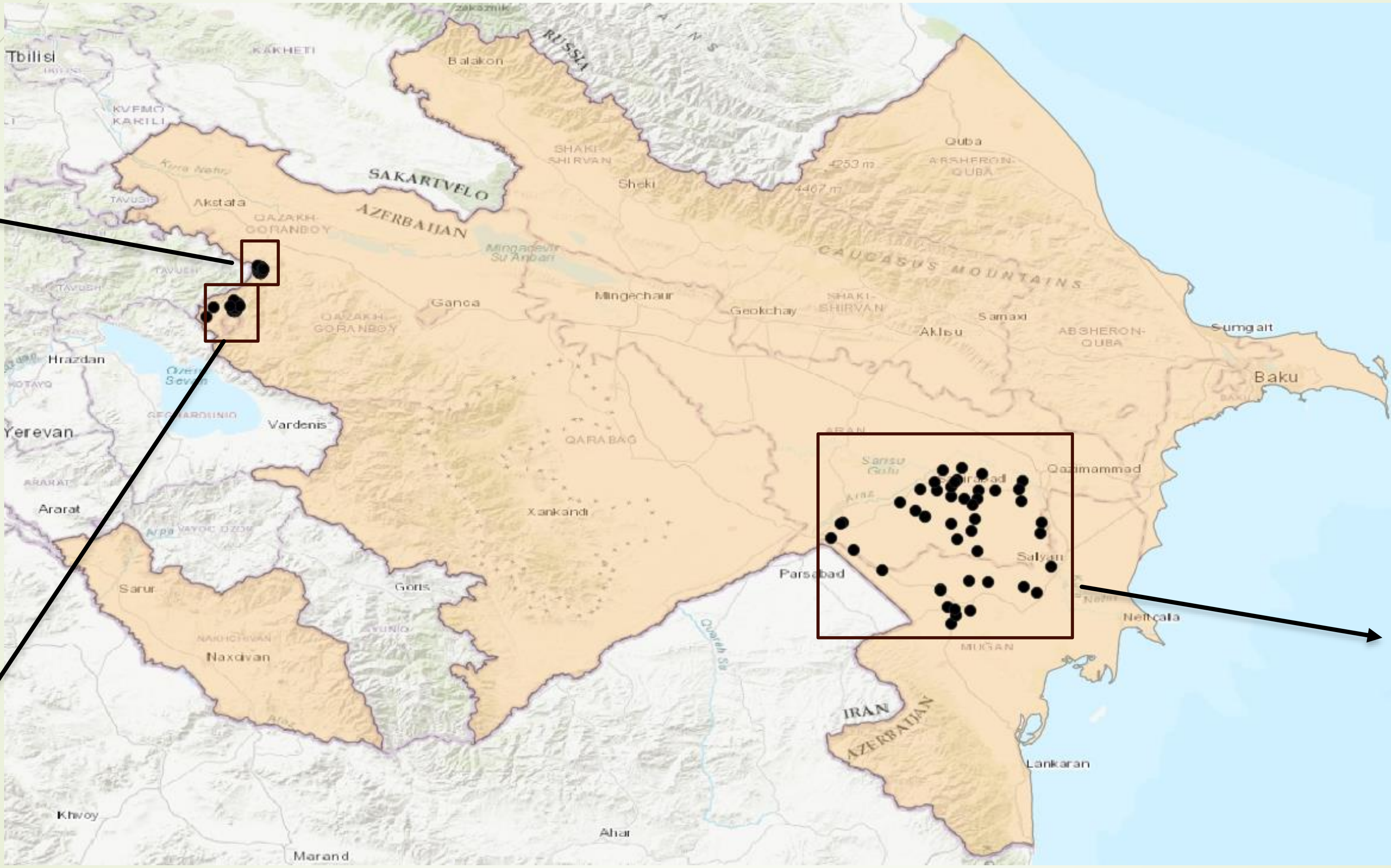
Mountain Land
Vis-NIR and MIR-FTIR
Sample: 114
17 soil properties
Elevation: 750-1000m



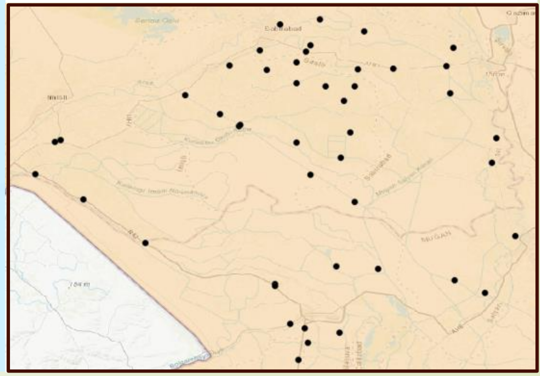
Mountain Land
Vis-NIR
Sample:101
16 soil properties
Elevation: 1450-2000m



Sampling coverage of Vis-NIR and MIR spectra prediction in Azerbaijan



Plain Land
Vis-NIR
Sample: 139
Soil property: 12
Elevation: - 20-25 m



Vis-NIR & MIR (FTIR) spectra for soil property prediction

land

MDPI

Article

Predicting Soil Properties for Agricultural Land in the Caucasus Mountains Using Mid-Infrared Spectroscopy

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Abstract: Visible-near infrared (Vis-NIR) and mid-infrared (MIR) spectroscopy are increasingly being used for the fast determination of soil properties. The aim of this study was (i) to test the use of MIR spectra (Agilent 4300 FTIR Handheld spectrometer) for the prediction of soil properties and (ii) to compare the prediction performances of MIR spectra and Vis-NIR (ASD FieldSpecPro) spectra; the Vis-NIR data were adopted from a previous study. Both the MIR and Vis-NIR spectra were coupled with partial least squares regression, different pre-processing techniques, and the same 114 soil samples, collected from the agricultural land located between boreal forests and semi-arid steppe belts (Kastanozems). The prediction accuracy ($R^2 = 0.70$–0.99) of both techniques was similar for most of the soil properties assessed. However, (i) the MIR spectra were superior for estimating $CaCO_3$, pH, SOC, sand, Ca, Mg, Cd, Fe, Mn, and Pb. (ii) The Vis-NIR spectra provided better results for silt, clay, and K, and (iii) the hygroscopic water content, Cu, P, and Zn were poorly predicted by both methods. The importance of the applied pre-processing techniques was evident, and among others, the first derivative spectra produced more reliable predictions for 11 of the 17 soil properties analyzed. The spectrally active $CaCO_3$ had a dominant contribution in the MIR predictions of spectrally inactive soil properties, followed by SOC and Fe, whereas particle sizes and hygroscopic water content appeared as confounding factors. The estimation of spectrally inactive soil properties was carried out by considering their secondary correlation with carbonates, clay minerals, and organic matter. The soil information covered by the MIR spectra was more meaningful than that covered by the Vis-NIR spectra, while both displayed similar capturing mechanisms. Both the MIR and Vis-NIR spectra seized the same soil information, which may appear as a limiting factor for combining both spectral

check for updates

Citation: Mammadov, E.; Denk, M.; Mamedov, A.I.; Glaesser, C. Predicting Soil Properties for Agricultural Land in the Caucasus Mountains Using Mid-Infrared Spectroscopy. *Land* **2024**, *13*, 154. https://doi.org/10.3390/land13020154

Soil Property	Wavelength range	Cross-validation (n=114)		
		RMSE	R^2	RPD
$CaCO_3$ (%)	MIR	0.36	0.99	6.68
	Vis-NIR	0.81	0.96	2.97
Sand (%)	MIR	8.48	0.85	2.01
	Vis-NIR	8.18	0.81	2.08
Silt (%)	MIR	5.51	0.81	2.01
	Vis-NIR	5.32	0.82	2.07
Clay (%)	MIR	4.14	0.79	1.69
	Vis-NIR	3.78	0.84	1.85
SOC (%)	MIR	0.41	0.95	2.86
	Vis-NIR	0.45	0.93	2.53
pH	MIR	0.22	0.90	1.94
	Vis-NIR	0.36	0.69	1.44
WC (%)	MIR	0.60	0.79	1.62
	Vis-NIR	0.72	0.63	1.38
Ca (mg kg^{-1})	MIR	131.50	0.92	2.96
	Vis-NIR	180.60	0.91	2.15
Cd (mg kg^{-1})	MIR	0.03	0.82	1.94
	Vis-NIR	0.035	0.80	1.81
Cu (mg kg^{-1})	MIR	0.30	0.58	1.35
	Vis-NIR	0.275	0.80	1.47
Fe (mg kg^{-1})	MIR	10.59	0.89	2.21
	Vis-NIR	14.66	0.82	1.60
K (mg kg^{-1})	MIR	89.01	0.78	1.43
	Vis-NIR	72.21	0.85	1.85
Mg (mg kg^{-1})	MIR	50.30	0.84	1.85
	Vis-NIR	67.14	0.73	1.39
Mn (mg kg^{-1})	MIR	13.27	0.87	1.79
	Vis-NIR	13.72	0.85	1.73
P (mg kg^{-1})	MIR	2.32	0.60	1.29
	Vis-NIR	2.19	0.73	1.36
Pb (mg kg^{-1})	MIR	0.35	0.93	2.45
	Vis-NIR	0.37	0.91	2.29
Zn (mg kg^{-1})	MIR	0.74	0.53	1.22
	Vis-NIR	0.75	0.56	1.20

Summary / Conclusions

- **National scale soil mapping emerges a promising technique for sustainable soil management:**

Soil health, sustainability, monitoring, yield prediction etc.

- **Field scale soil mapping techniques could reliably support precision agriculture and sustainable soil management**

Soil property mapping allows to track the changes in soil and reduce fertilizer and pest application using variable rate technologies

- **Soil spectroscopy is a crucial technique for developing countries to develop the national soil information system that could contribute to soil management**

Thanks for your attention!

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