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URBANİZATİON AND CLİMATE CHANGE

REPUBLIC OF TURKEY
MINISTRY OF ENVIRONMENT,
URBANIZATION AND CLIMATE CHANGE

General Directorate of Combating Desertification and Erosion

TOPRAK ORGANİK
KARBONU PROJESİ

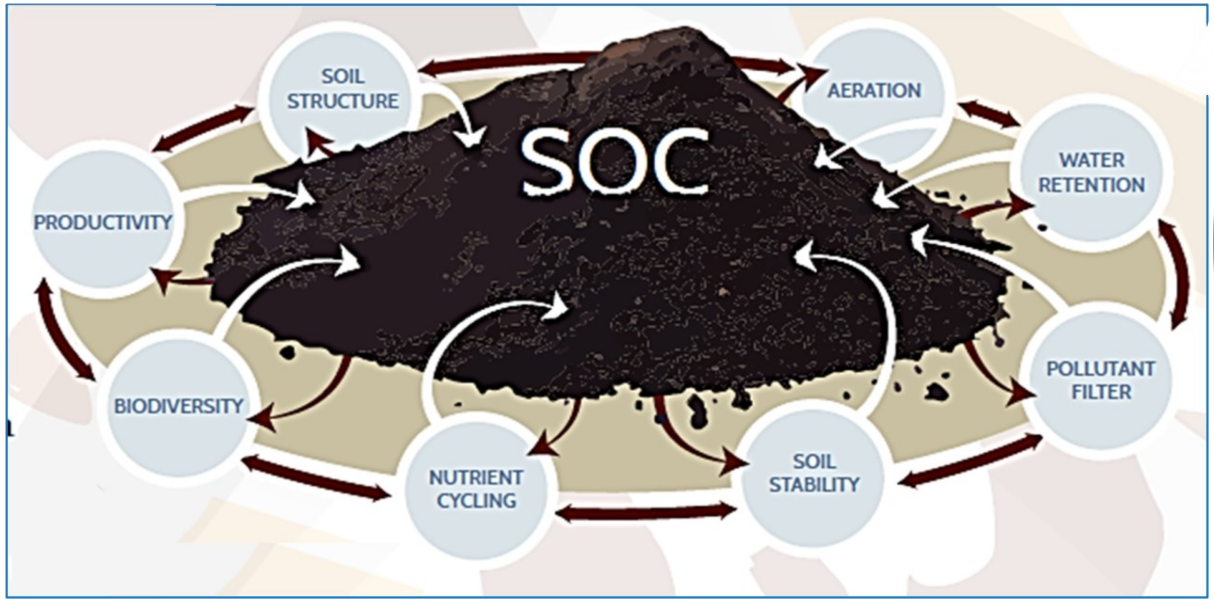
Soil Organic Carbon Modeling and Mapping of Turkey

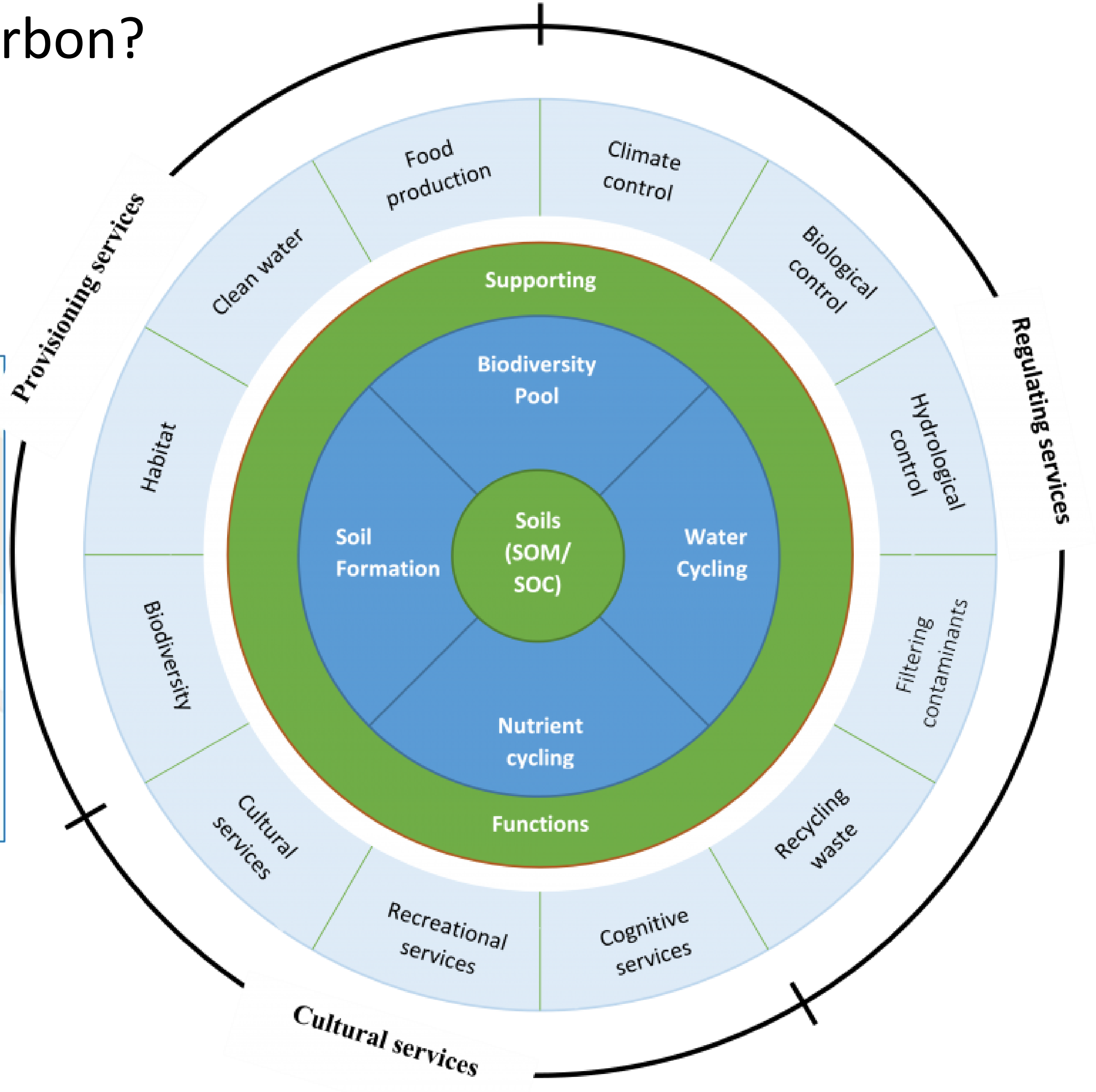
Hamza KESKİN

Department of Combating Desertification

10 Agust 2024 I Ankara I Turkey

Why Soil Organic Carbon?





Where are SOC data needed?

Food and Agriculture Organization of the United Nations

SDG (2.4, 15.2, **15.3**)
Rio+20

LDN target setting
National Action Programmes (NAPs)
UNCCD

UNCCD
United Nations Convention to Combat Desertification

UNCBD/IPBES
National Biodiversity Strategies and Action Plans (NBSAPs), Aichi Targets

Convention on Biological Diversity

SOC INDICATORS

United Nations Framework Convention on Climate Change

UNFCCC/IPCC
IPCC AR, **GHG** (MRV) (AFOLU), INDC, REDD+

GLOBAL SOIL PARTNERSHIP

GSP
UN World Soil Charter
Voluntary Guidelines for SSM
Status of the World's Soil Resources Report
Global Soil information System and SoilSTAT

UN-FAOSTAT
FAO STAT (**agro-env indicators** and UN statistics), Agriculture productivity

Goal

- ✓National scale, dynamic, updateable, interpretable, parsiminous, data driven soil organic carbon model
- ✓Uncertainity specified, most accurate soil carbon data(ton/ha-1)
- ✓Reference SOC value for different landuses, soil orders, administration boundaries
- ✓SOC monitoring system

TOPRAK ORGANİK KARBONU PROJESİ

Coordination Meetings

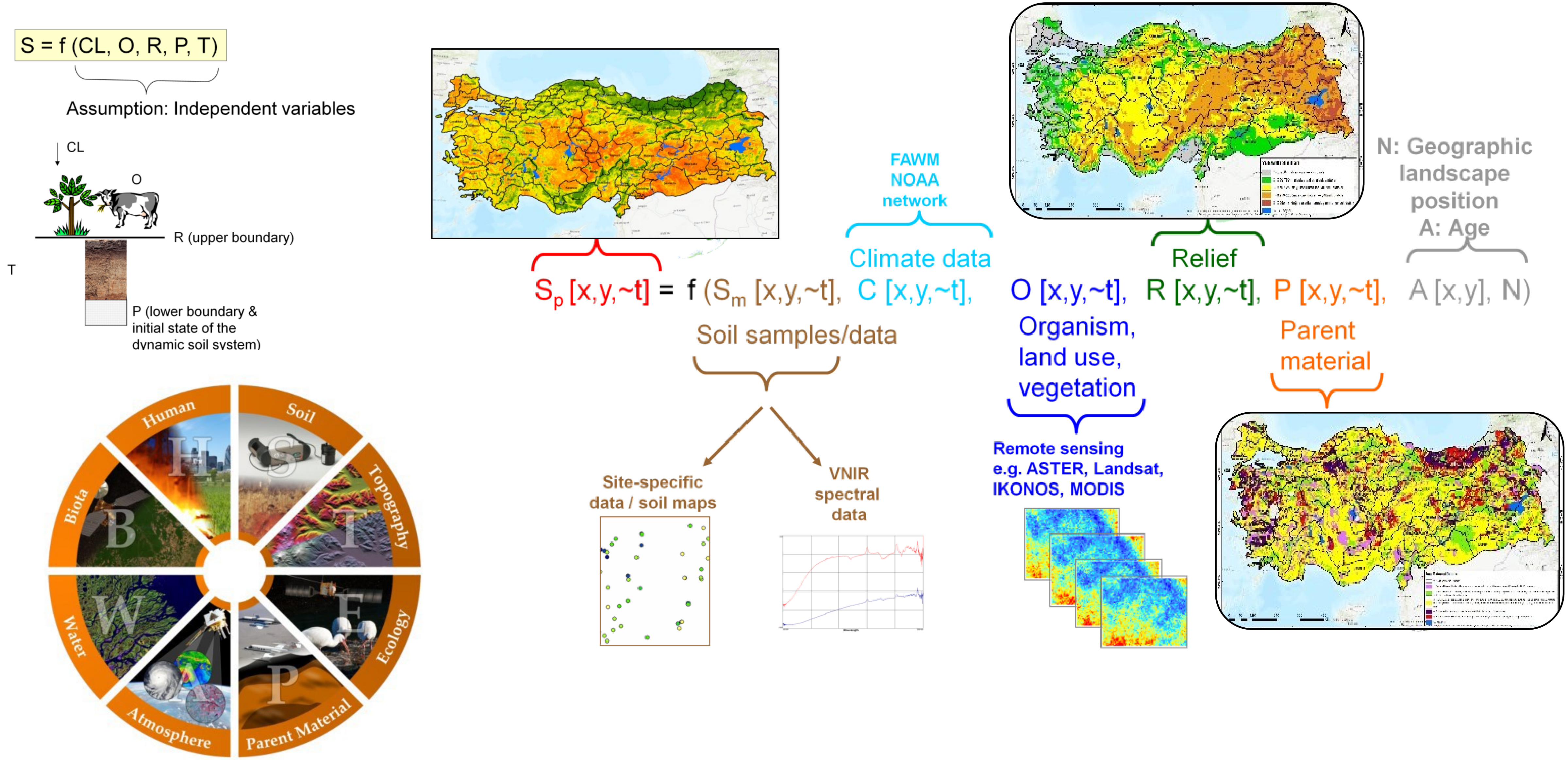






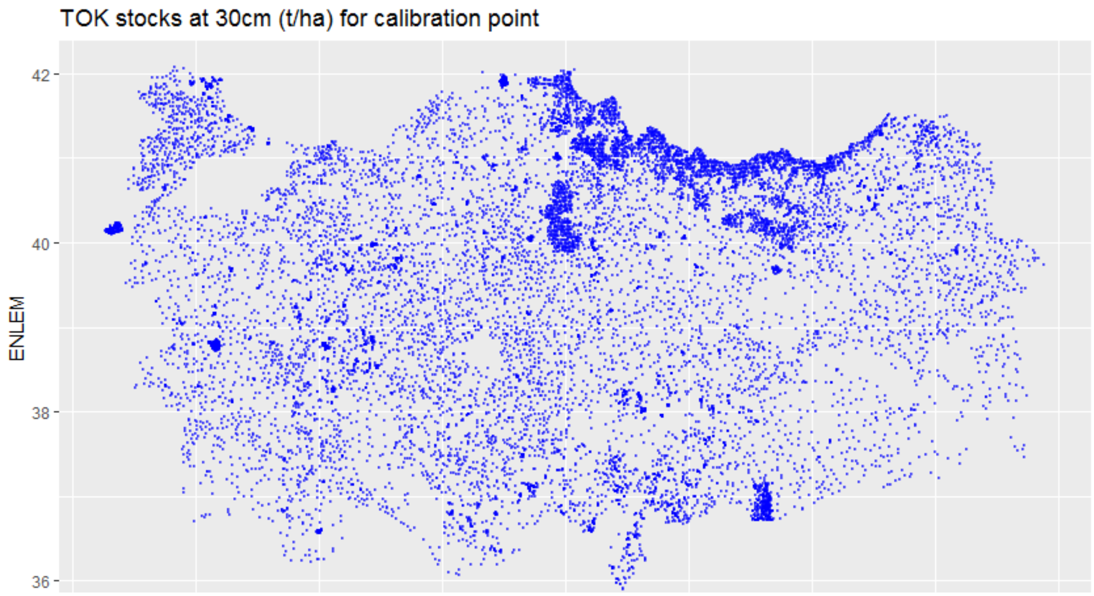


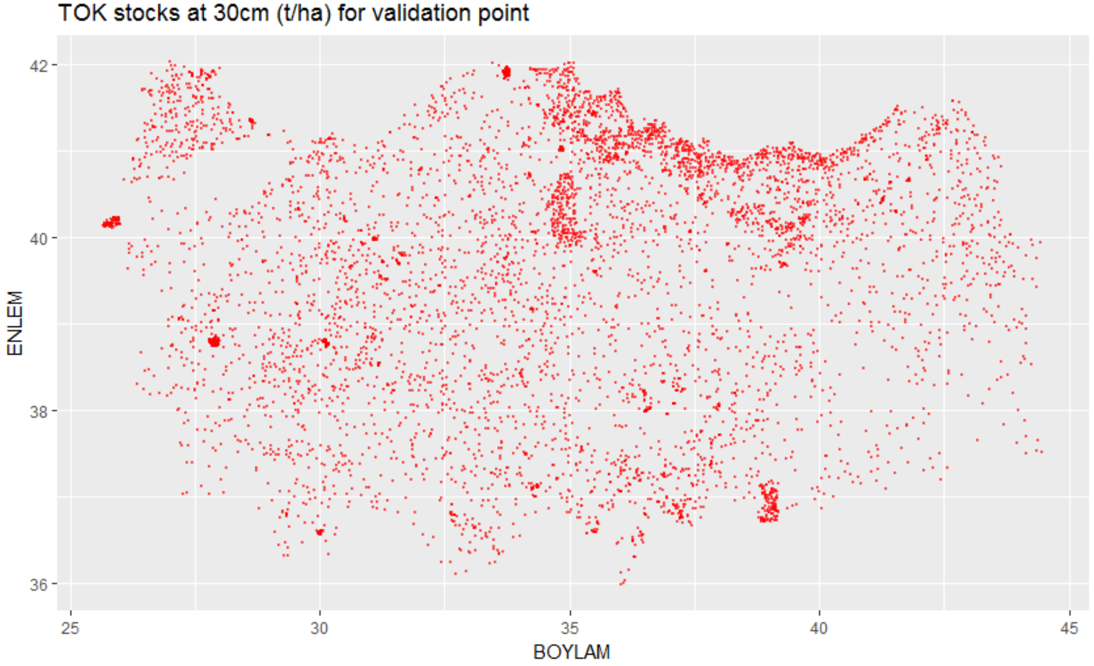
Modeling Framework



Dokuachev,1880; Jenny, 1941; McBratney et al. 2003, Grunwald, 2011

Standardized Soil Organic Carbon Data





A total of 20187 soil samples collected

1. Quality checked

✓ 1.Coordinates

✓ 2. false data

✓ 3. repeatetive data

2. Depth calculation

✓ 0-30cm

3. Missing value computation

✓ Bulk density etc.

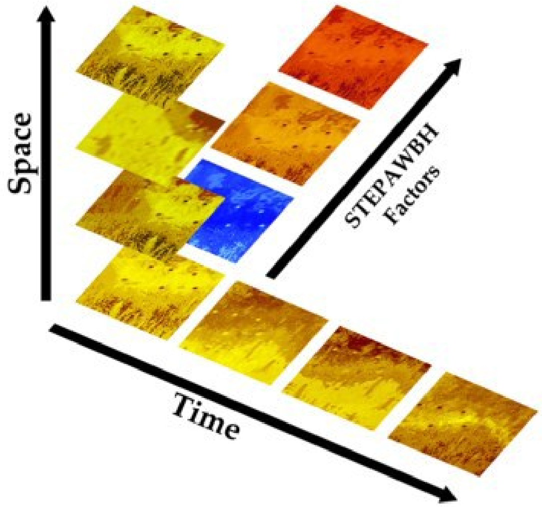
4. Conversion to stock

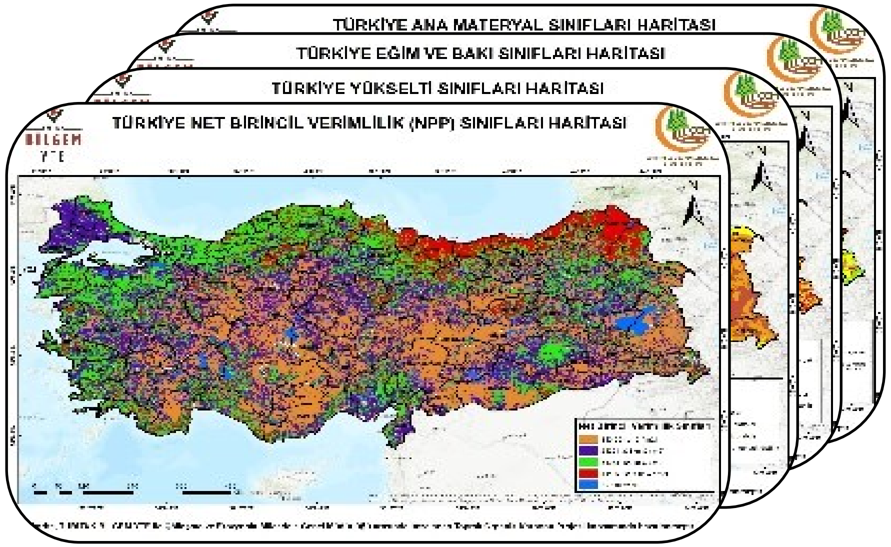
✓ Stonnines

✓ Ton/ ha

5. Outlier analysis

Environmental Factors





...

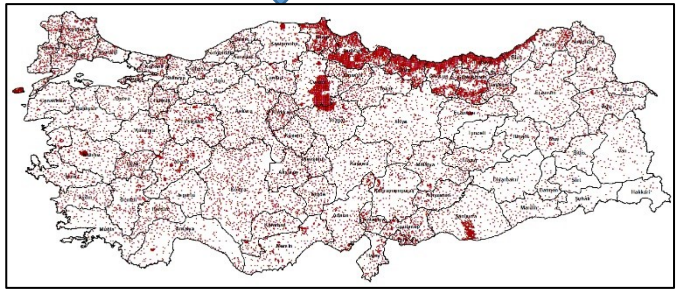
A total of 260 Environmental variables obtained and standardized to use as covariates

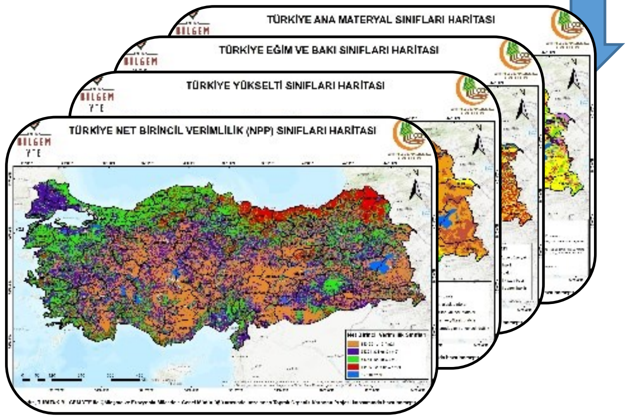
- CORİNE LULC 2015
- MODIS derivatives
- SRTM
- WorldClim
- SoilGrids

Selected minimum optimal environmental variables

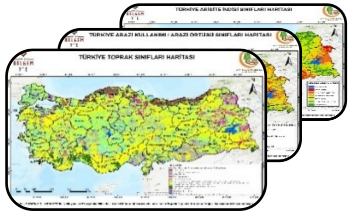
SOC data

Covariates





Selected Minimum optimum covariates from Boruta.



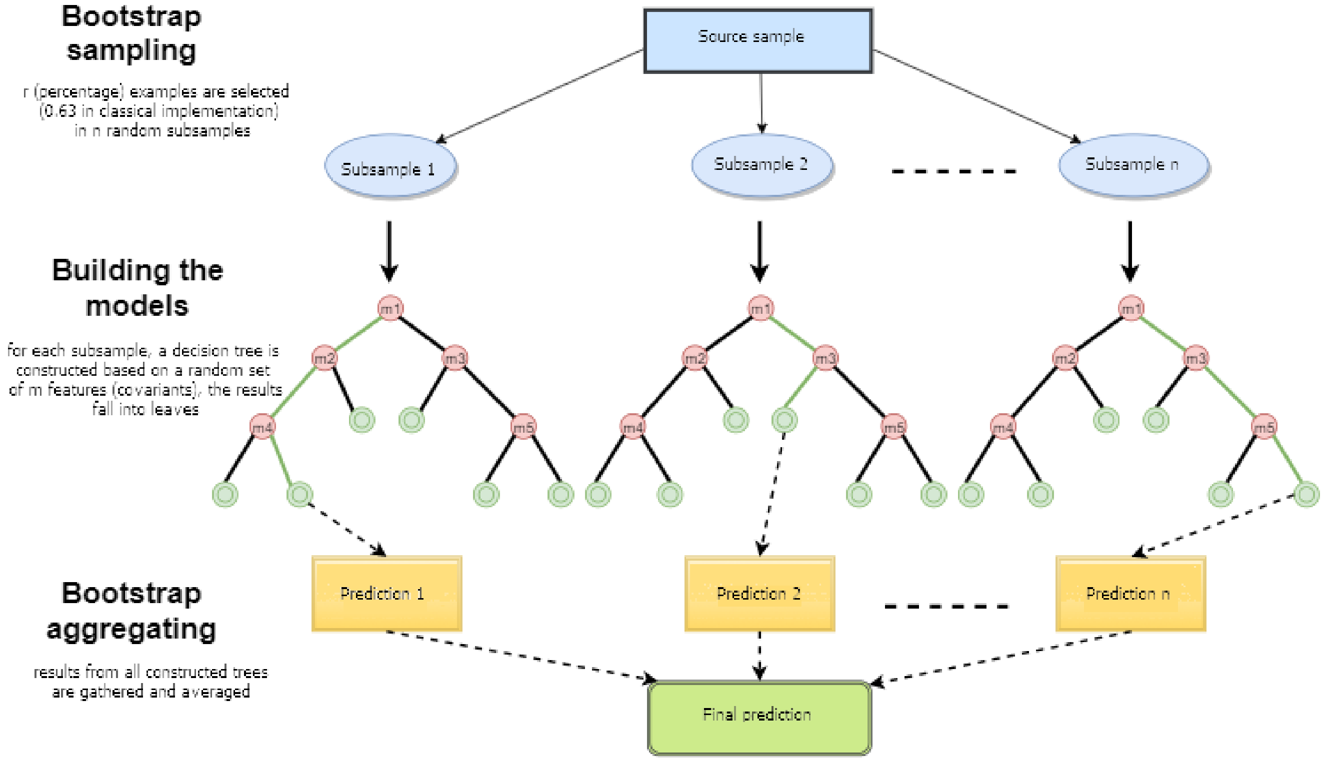
Multicollinearity between minimal-optimal variables

Selected minimal optimal

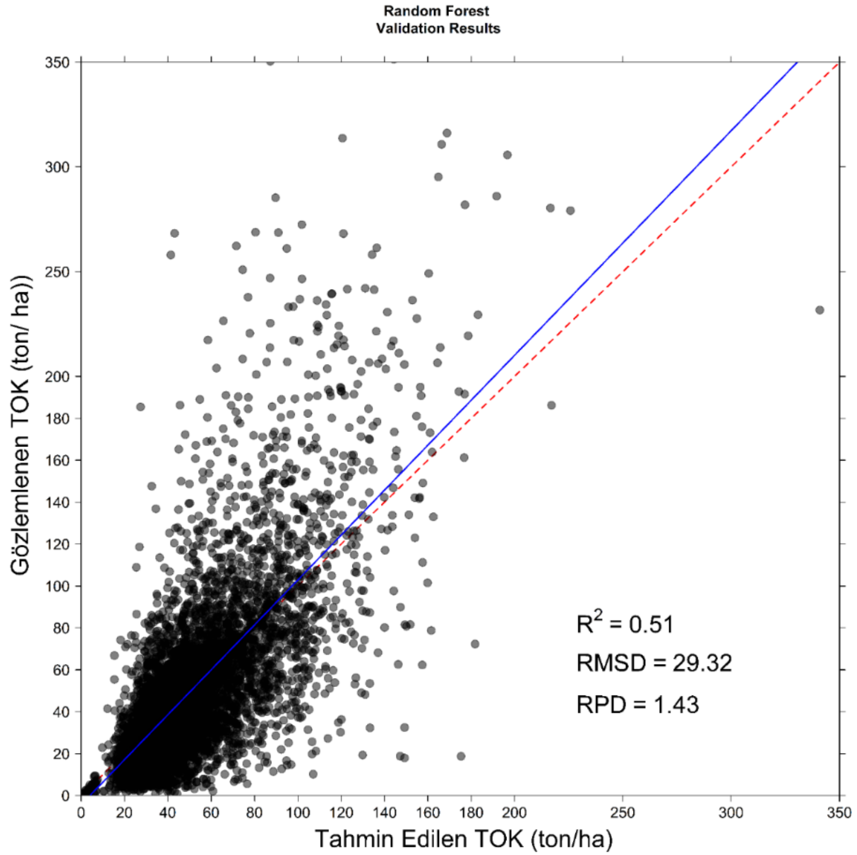
Minimum Optimal Variables

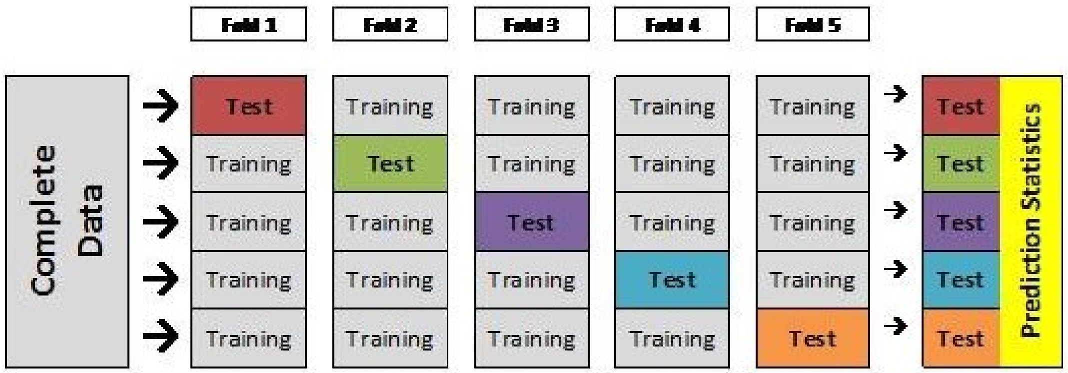
No	Variable name	Unit	Source	Time
1	**Slope**	%	SRTM	2014
2	**Valley Depth**	Meter	SRTM	2014
3	**Terrain Roughness Index**	İndis	SRTM	2014
4	**Maksimum Temperature**	°C	Global Climate Data	1970-2000
5	**Temperature Seasonality**	İndex	Global Climate Data	1970-2000
6	**İsotermality**	kJ m^{-2} day^{-1}	Global Climate Data	1970-2000
7	**Conrad Aridity ndex**	İndex	MGM	Uzun Süreli
8	**Precipitation**	Milimeter	Global Climate Data	1970-2000
9	**Precipitation of Wettest Quarter**	Milimeter	Global Climate Data	1970-2000
10	**Precipitation of Coldest Quarter**	Milimetre	Global Climate Data	1970-2000
11	**Potential Evapotranspiration**	kg/m^2	MODIS	2010 – 2015
12	**Net Primary Productivity**	g C/m2/year	MODIS	2010 - 2014
13	**Net Primary Productivity (June)**	g C/m2/year	MODIS	2010 - 2014
14	**Tree Canopy Cover**	%	MODIS	2010 – 2015
15	**Surface Reflection**	İndex	MODIS	2010 - 2015
16	**CORINE LULC**	İndex	CORINE, Amenajman Planları, Mera haritaları	1973-2017

Machine Learning Algorithms –Random Forest



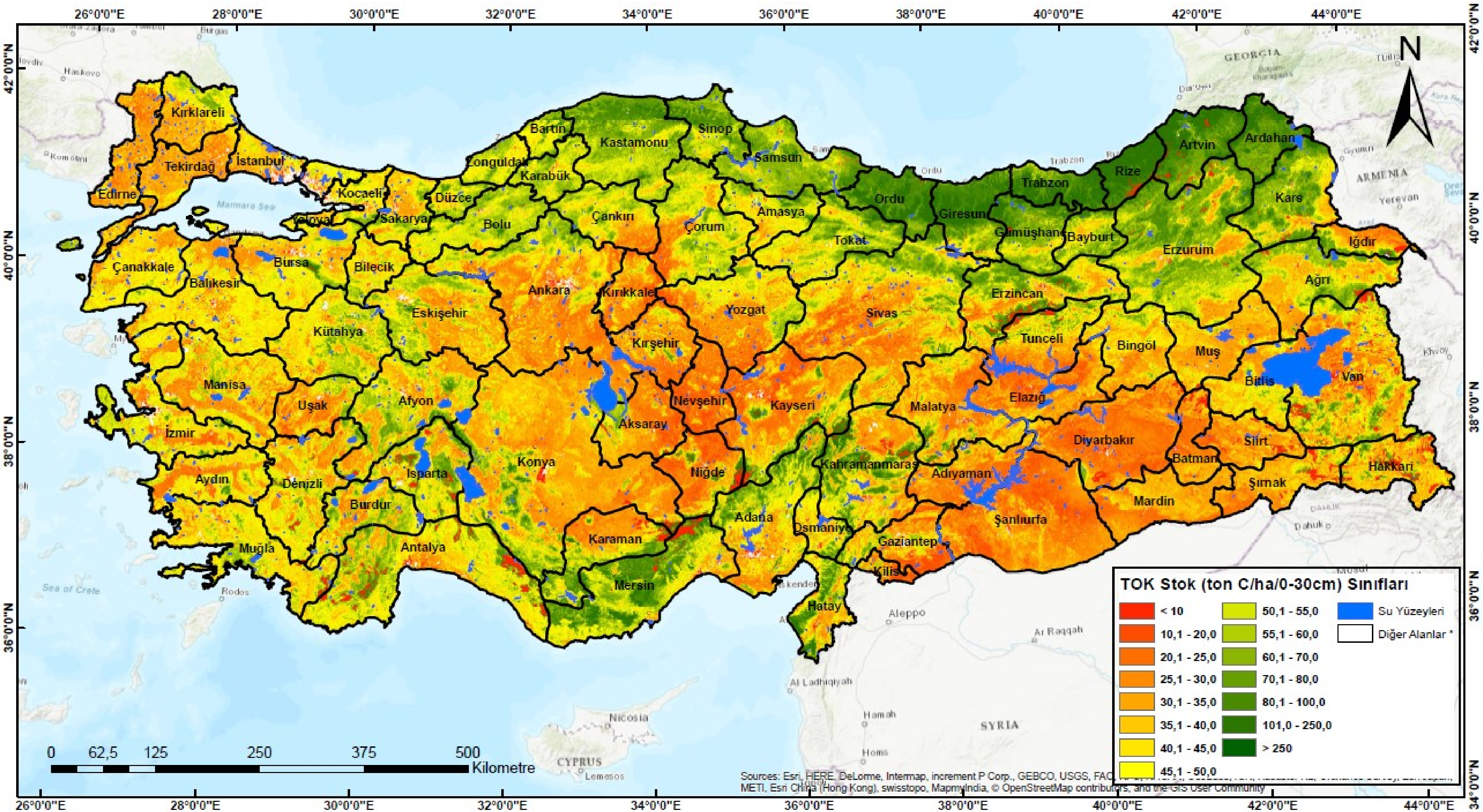
1. Build many deep decision trees on bootstrapped training datasets
2. A different subset of the training data are selected (~2/3), with replacement, to train each tree
3. For each tree, only consider a random subset of predictors ($\approx \sqrt{p}$ is typical)
4. Average the predictions from all individual decision trees
5. Options to calculate error and variable significance information
6. Remaining training data (OOB) are used to estimate error and variable importance





Modeling Approach	• Machine Learning
Algorithm	• Random Forest
Programming Language	• R
Soil data size	• 20.187 (0-30 cm)
Training data size	• 14.131 (%70)
Validation data size	• 6.056 (%30)
No of Covariates	• 260
Minimum-Optimal Covariates	• 16
Cross Validation	• 15 Fold Cross-Validation
Nof of Pixel	• 12.506.280 (250m x 250m)
R2	• 0.42

SOC(0-30cm) stocks map of Turkey



Bu harita, TÜBİTAK BİLGEM YTE ile Çölleşme ve Erozyonla Mücadele Genel Müdürlüğü arasında imzalanan Toprak Organik Karbonu Projesi kapsamında hazırlanmıştır. Harita 250m mekansal çözünürlüğüe sahip olup, Toplam TOK Stoku (0-30cm) = 3.516 milyar ton C dur.

*** Diğer Alanlar: Sürekli Şehir Yapısı, Endüstriyel ve Ticari Birimler, Karayolları, Demiryolları, Limanlar, Havaalanları, Maden Çıkarım Sahaları, Boşaltım Sahaları, İnşaat Sahaları ile Yüksekliği 3501m ve üstünde olan alanlar**

LULC-Level I

No	LULC level 1	Area (ha)	Area (%)	Mean SOC (t C/ha)	Total SOC Stocks (t C)	Total SOC Stocks (%)
1	Forest	24.180.644	31,64	55,68	1.346.434.101	38,33
2	Pastures	23.568.338	30,84	49,77	1.172.981.521	33,39
3	Agricultural areas	26.316.375	34,43	35,96	946.317.555	26,94
4	Bare rocks	1.172.581	1,53	12,78	14.981.558	0,43
5	Artificial Surfaces	796.519	1,04	16,12	12.838.873	0,37
6	Wetland and water surfaces	393.100	0,51	49,71	19.542.037	0,56

Forest Canopy Cover

Canopy Cover Classes	Mean SOC Stocks (t C/ha)
% 0 - 10,0	
Deciduous forest	49,53
Coniferous forest	54,41
Mixed forest	56,64
%10,1 - 40,0	
Deciduous forest	56,98
Coniferous forest	54,28
Mixed forest	58,34
%40,1 - 70,0	
Deciduous forest	66,23
Coniferous forest	60,46
Mixed forest	73,58
%70,1 - 100,0	
Deciduous forest	77,89
Coniferous forest	70,81
Mixed forest	86,63

Watershed Level SOC stocks

No	Watershed	Area(ha)	Area(%)	SOC Stocks (t C/ha)	Total SOC Stocks (t C)	Total SOC Stocks (%)
1	Doğu Karadeniz	2.286.346	2,96	100,68	230.189.314	6,56
2	Çoruh	2.044.062	2,64	71,81	146.784.079	4,18
3	Doğu Akdeniz	2.721.549	3,52	63,12	171.784.168	4,89
4	Aras	2.215.831	2,86	61,39	136.029.853	3,87
5	Batı Karadeniz	2.858.482	3,70	60,92	174.138.710	4,96
6	Yeşilırmak	3.933.104	5,09	56,79	223.360.978	6,36
7	Asi	770.599	1,00	53,5	41.227.042	1,17
8	Ceyhan	1.921.702	2,48	48,56	93.317.833	2,66
9	Antalya	1.988.581	2,57	47,92	95.292.821	2,71
10	Seyhan	756.758	0,98	47,45	35.908.170	1,02
11	Akarçay	596.150	0,77	47,36	28.233.660	0,8
12	Batı Akdeniz	865.172	1,12	46,29	40.048.807	1,14
13	Burdur	2.320.353	3,00	43,37	100.633.697	2,87
14	Susurluk	2.372.541	3,07	43,11	102.280.256	2,91
15	Sakarya	2.435.851	3,15	42,72	104.059.544	2,96
16	Küçük Menderes	2.561.997	3,31	42,38	108.577.454	3,09
17	Büyük Menderes	616.048	0,80	42,34	26.083.484	0,74
18	Kuzey Ege	2.143.509	2,77	41,43	88.805.578	2,53
19	Marmara	6.447.059	8,34	41,36	266.650.378	7,6
20	Gediz	1.688.969	2,18	39,88	67.356.086	1,92
21	Kızılırmak	1.364.545	1,76	39,43	53.804.008	1,53
22	Van Gölü	8.483.001	10,97	37,75	320.233.281	9,12
23	Konya Kapalı	1.331.810	1,72	36,37	48.437.923	1,38
24	Fırat ve Dicle	17.487.178	22,61	36,19	632.860.967	18,03
25	Meriç Ergene	5.133.745	6,64	34,03	174.701.352	4,98

Cities level SOC Stocks

No	İl Adı	TOK Miktarı (t C/ha)	TOK Stoğu (t C)
1	Rize	111,75	44.206.182
2	Trabzon	102,12	47.408.096
3	Ordu	94,42	55.179.545
4	Artvin	88,15	63.530.608
5	Giresun	90,66	63.495.958
...	...	...	...
...	...	...	...
...	...	...	...
77	Niğde	32,82	22.970.071
78	Kilis	31,35	4.298.935
79	Şanlıurfa	27,24	51.521.050
80	Diyarbakır	26,10	39.651.079
81	Nevşehir	24,39	13.541.283

Questions?

Thank you for your attention

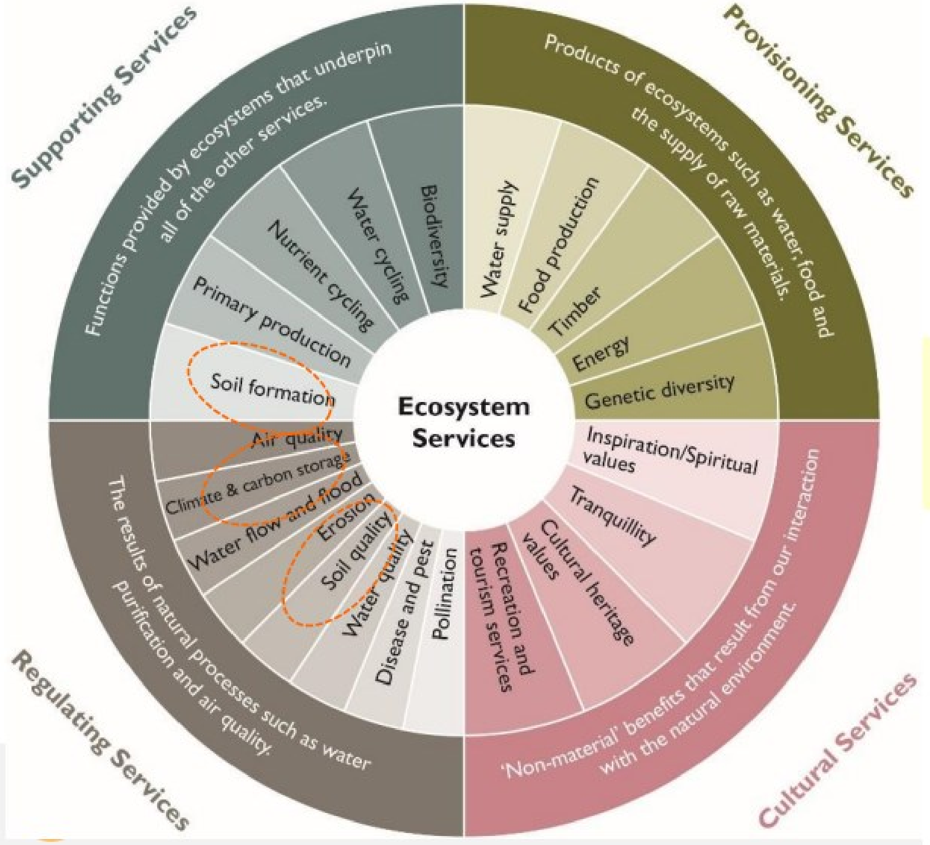
Global **scale**

National scale

Local scale/ farmers

- improvements in global climate change
- enhanced carbon sequestration
- enhanced biodiversity
- enhanced tourism
- improvement of environmental issues (air and water quality
- enhanced agricultural sustainability
- enhanced food security
- enhanced resource base for future generations
- decrease of soil degradation
- enhanced crop, timber, livestock yields
- soil and food quality

Maintaining SOC storage at an equilibrium or increasing SOC content towards the optimal level for the local environment can contribute to achieving the SDGs; also UNFCCC, UNCCD, and Paris Agreement



Article preview

Abstract

Section snippets

References (126)

Cited by (127)

Geoderma
Volume 326, 15 September 2018, Pages 22-41

Regression kriging as a workhorse in the digital soil mapper's toolbox ☆

H. Keskin [a] [b], S. Grunwald [a]

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https://doi.org/10.1016/j.geoderma.2018.04.004

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Geoderma
Volume 339, 1 April 2019, Pages 40-58

Digital mapping of soil carbon fractions with machine learning

Hamza Keskin [a] [b], Sabine Grunwald [a], Willie G. Harris [a]

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https://doi.org/10.1016/j.geoderma.2018.12.037

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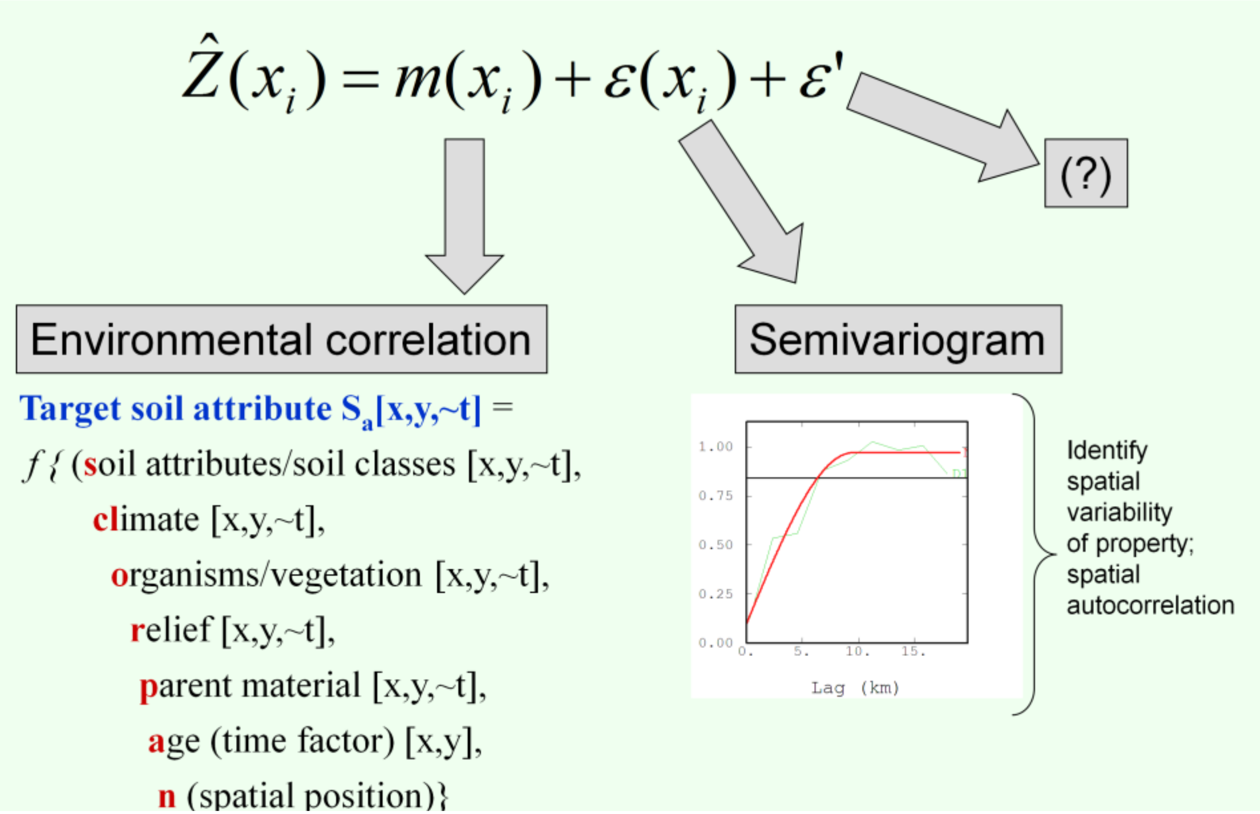
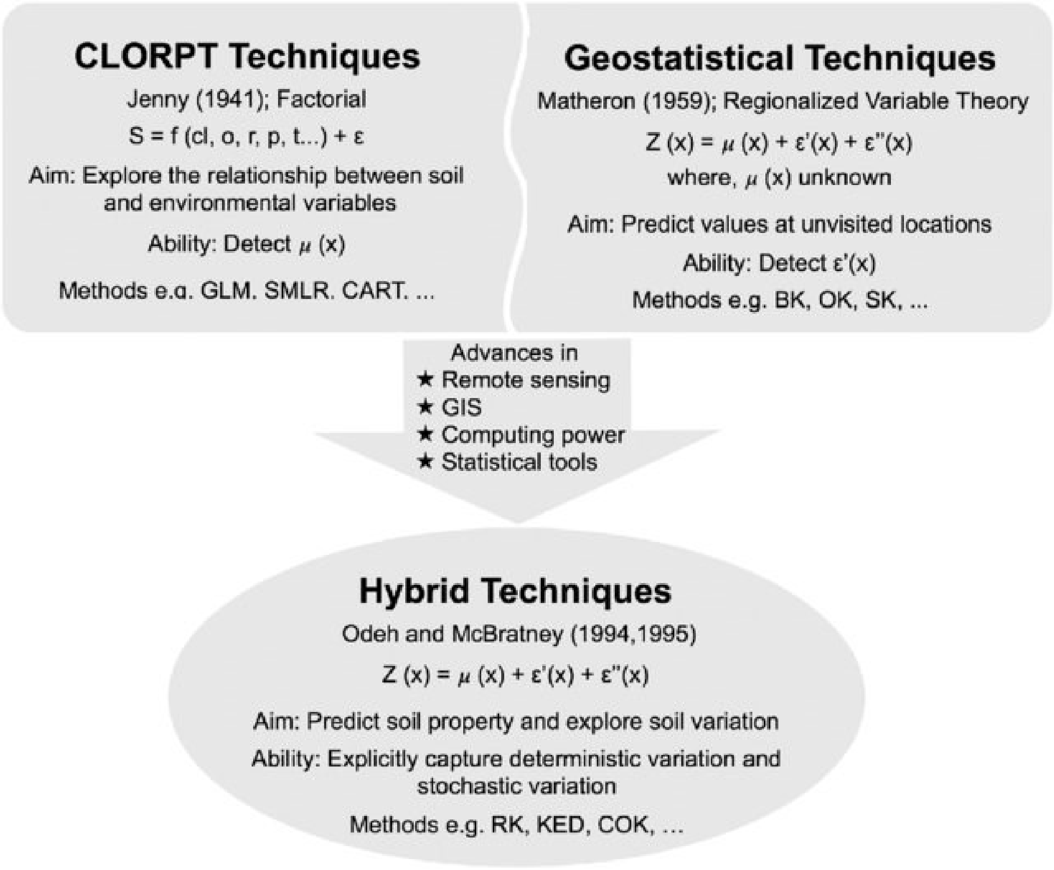
Sources of Georeferenced Soil Samples

Source	No of Soil Samples	Source	No of Soil Samples
TAGEM Mera	3437	**ÇEM**	2925
TAGEM FAO	7468	**Trakya**	409
CORUM Havza I	312	**Denizli**	73
CORUM Havza II	282	**Ender MAKİNECİ**	164
Alper OZTURNA	13	**Sinanpaşa**	150
İstanbul Kumul	143	**Muş**	7
Elmalı	103	**OGM ICP Forest I**	720
Aydın ÇÖMEZ	63	**OGM ICP Forest II**	52
Yeniçağa	19	**OGM Akdeniz**	89
GAP-1	28	**Gediz**	319
Gökçeada	247	**İnebolu**	230
TAGEM Karadeniz	3400	**GAP-2**	408
		TOPLAM	**21061**

Soil Modeling and Mapping Methodology





Keskin and Grunwald, 2018

Which variable are most useful?

- How do we decide which variables are most useful in predicting the response?
  - We can compute something called relative influence plots.
  - These plots give a score for each variable.
  - These scores represents the decrease in MSE when splitting on a particular variable
  - A number close to zero indicates the variable is not important and could be dropped.
  - The larger the score the more influence the variable has.

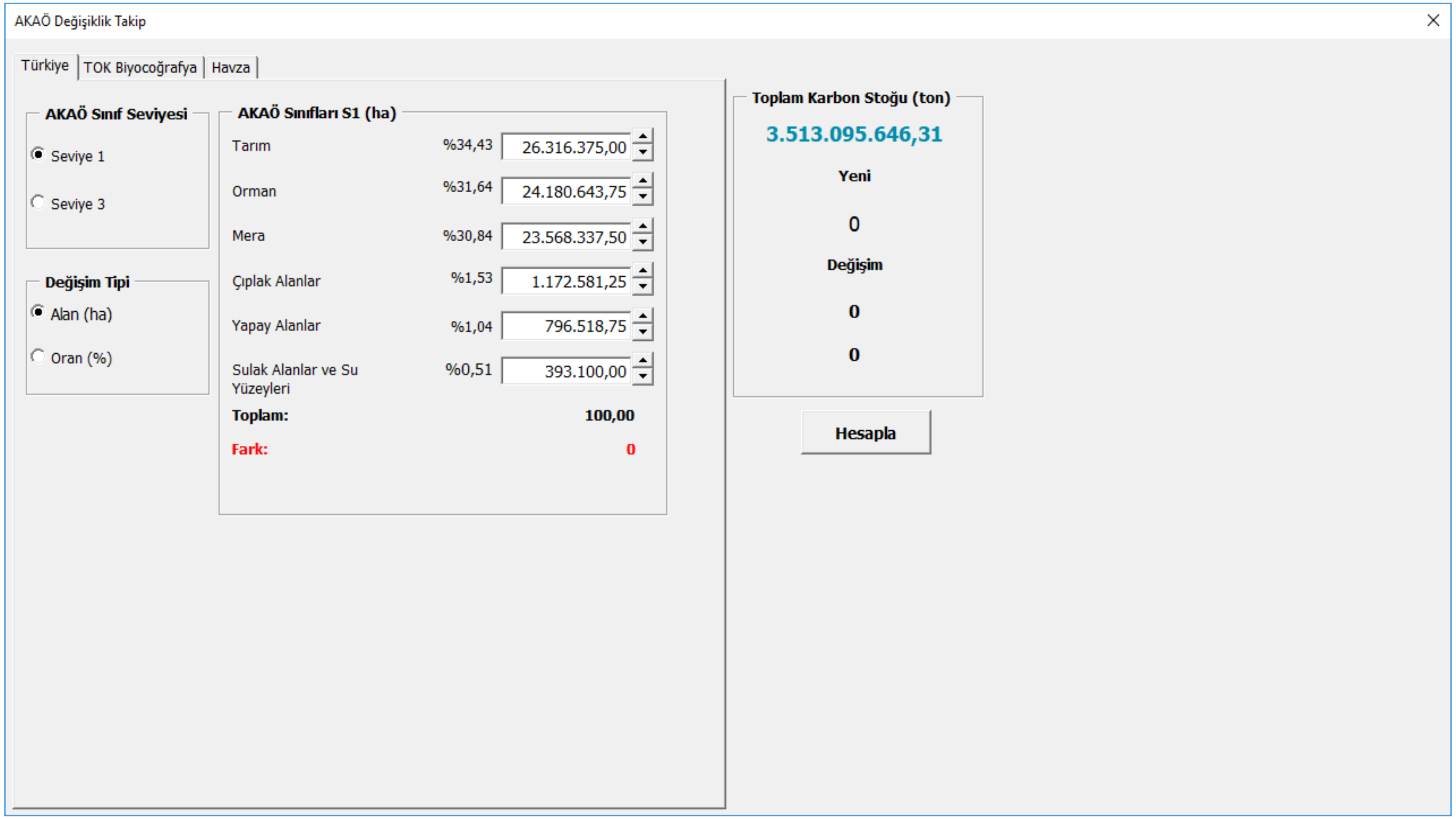
Why are we considering a random sample of m predictors instead of all p predictors for splitting?

- Suppose that we have a very strong predictor in the data set along with a number of other moderately strong predictor, then in the collection of bagged trees, most or all of them will use the very strong predictor for the first split!

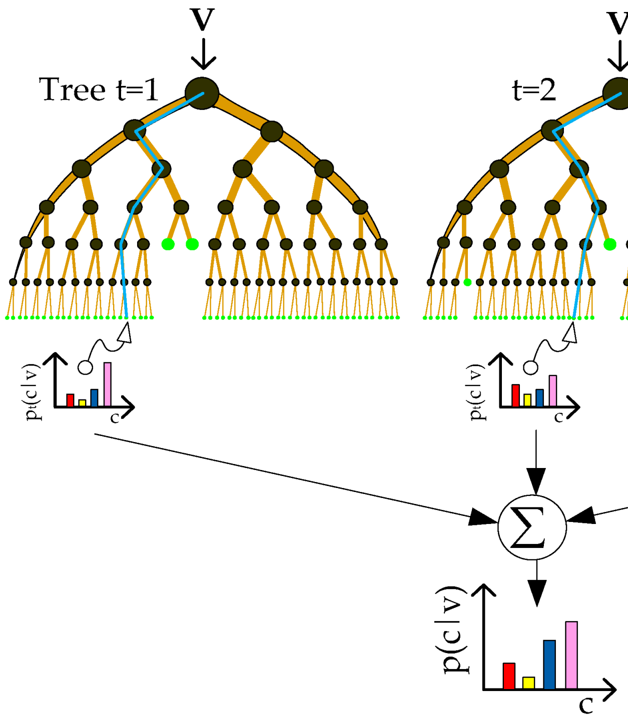
- All bagged trees will look similar. Hence all the predictions from the bagged trees will be highly correlated

- Averaging many highly correlated quantities does not lead to a large variance reduction, and thus random forests "de-correlates" the bagged trees leading to more reduction in variance

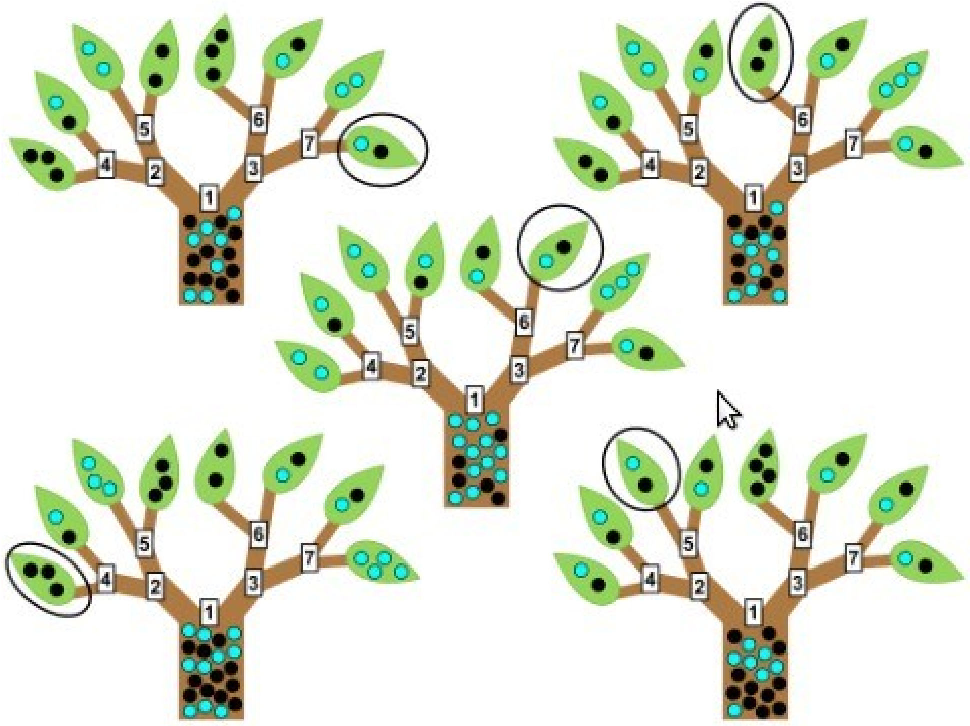
Nereden	Nereye	Ne Kadar (ha)	Değişim (t C)	Değişim (%)
Çıplak Alan	Orman	1 milyon	42.9 milyon	1.22
Mera	Tarım	1 milyon	-13,8 milyon	-0,39



No	Variable name	Unit	Source	Date
1	**Slope**	Metre	SRTM	2014
2	**Vadi Derinliği**	Metre	SRTM	2014
3	**Arazi Pürüzlülük İndeksi**	İndis	SRTM	2014
4	**Maksimum Sıcaklık**	°C	Global Climate Data	1970-2000
5	**Sıcaklık Mevsimselliği**	İndis	Global Climate Data	1970-2000
6	**Güneş Işınımı**	kJ m^{-2} $gün^{-1}$	Global Climate Data	1970-2000
7	**Conrad Karasallık İndisi**	İndis	MGM	Uzun Süreli
8	**Precipitation**	Milimetre	Global Climate Data	1970-2000
9	**En Nemli Çeyreğin Yağış Miktarı**	Milimetre	Global Climate Data	1970-2000
10	**En Soğuk Çeyreğin Yağış Miktarı**	Milimetre	Global Climate Data	1970-2000
11	**Potansiyel Evapotranspirasyon**	kg/m^2	MODIS	2010 – 2015
12	**Net Birincil Verimlilik**	g C/m2/yıl	MODIS	2010 - 2014
13	**Net Birincil Verimlilik (Temmuz)**	g C/m2/yıl	MODIS	2010 - 2014
14	**Ağaç Kapalılık Yüzdesi**	%	MODIS	2010 – 2015
15	**Yüzey Yansıması**	İndice	MODIS	2010 - 2015
16	**CORINE LULC**	İndice	CORINE, Amenajman Planları, Mera haritaları	1973-2017



V
Tree t=1
V
t=2
V
t=3
p(c|v)
c



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…	…	…	…
…	…	…	…
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80	Diyarbakır	26,10	39.651.079
81	Nevşehir	24,39	13.541.283

SOC Analyictal Dashboard