Soil attributes mapping: an experience from the dry areas

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Soil Survey Data

Limitation of soil maps:

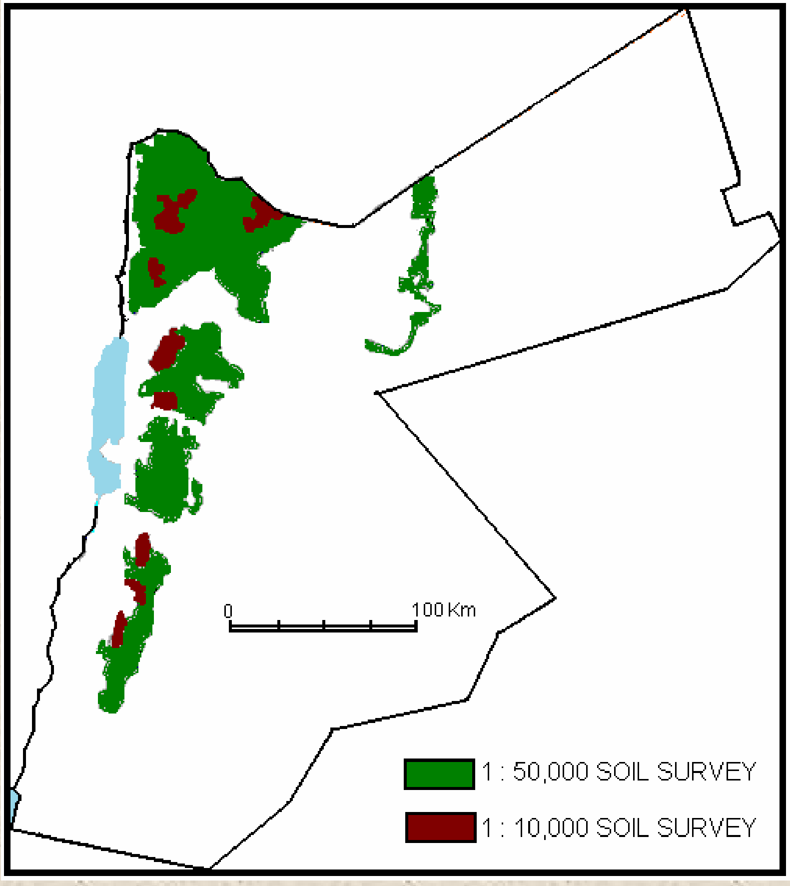
The coverage, especially with enough details, in dry areas is usually limited. The cost of extending this coverage is high.

Example: Jordan …

1:250,000: The whole country

1:50,000: 20 % of the country

1:10,000: 2 % of the country



Soil Survey Data

Limitation of soil maps:

The purity of mapping units is usually low, leads to erroneous conclusions when used for site-specific decisions

The accuracy of site-specific suitability using 1:10,000 scale soil map was only 60-70%

Modern environmental applications and modelling require information about the spatial distribution of lateral and vertical soil attributes

ALTERNATIVE SOURCES OF SOIL INFORMATION

Alternative sources of soil information

Developments in new technologies; GIS and remote sensing provide new approaches to meet the demand of resource-related modelling.

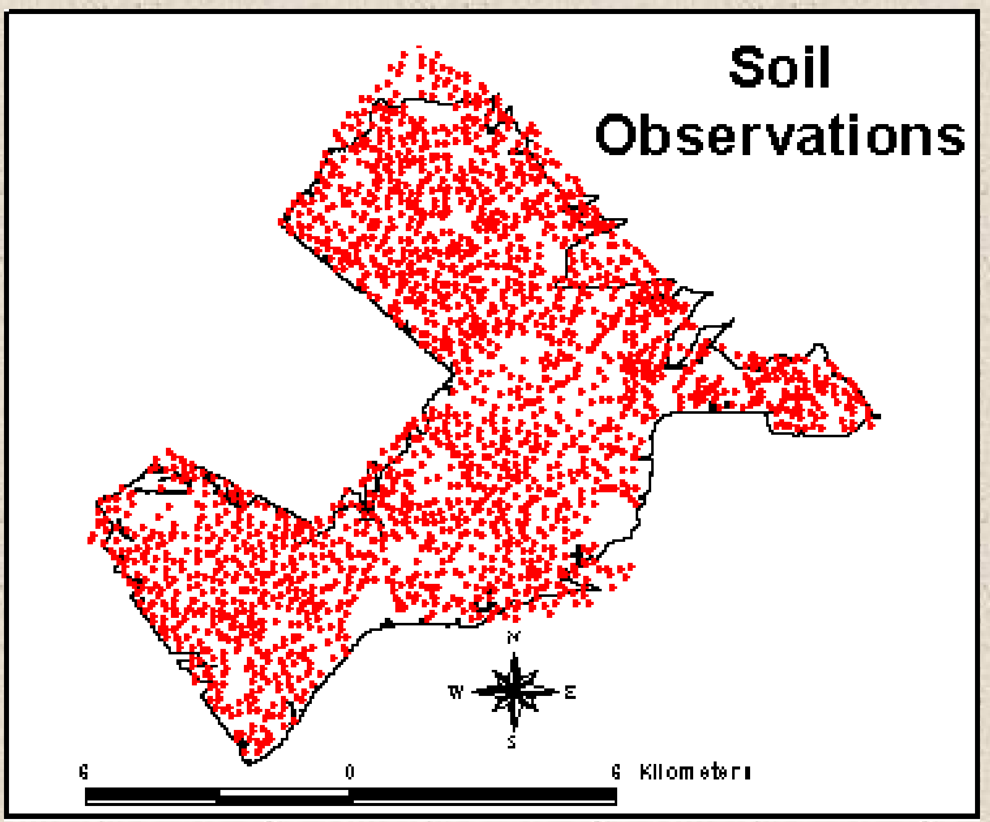
DEMs are used to derive landscape attributes, which is utilized in landforms characterization.

The derived topographic attributes control the soil differentiation through the form-process connections that is often addressed in geomorphology.

Prediction of soil attributes using terrain attributes

Terrain attributes derived from 20-m resolution DEM were utilized to predict soil attributes by implementing different statistical and clustering techniques.

Correlation between soil attributes and terrain attributes for 2193 field observations



Correlation and regression coefficients between soil attributes and terrain attributes (example for soil depth

Significant but low correlation

Low regression coefficients

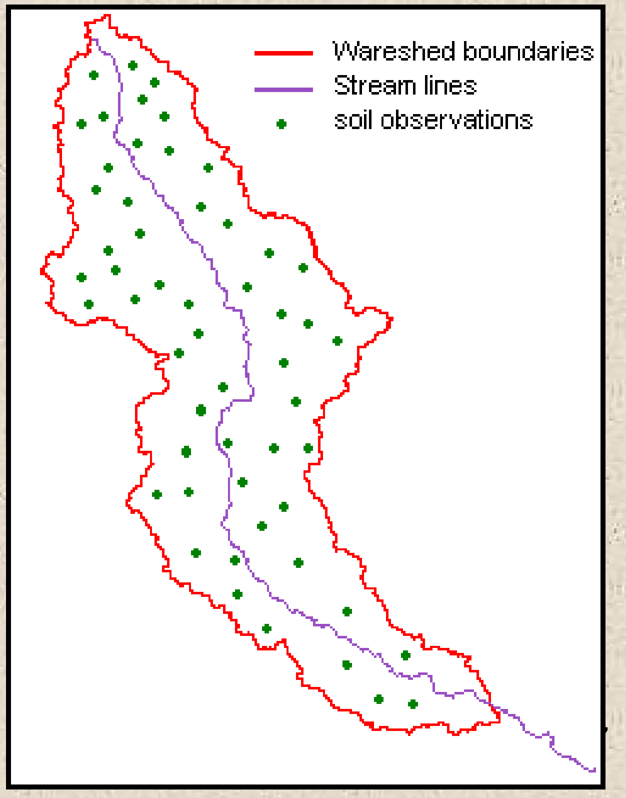
Terrain attribute	Soil depth
	cm
CTI†	−0.10**
Aspect	−0.15**
Curvature	−0.10*
Plan curvature	−0.05*
Profile curvature	−0.05*
Slope degree	−0.23**
Slope percent	−0.23**
Aspect (CA)‡	−0.10**
Curvature (CA)‡	−0.15**
Plan curvature (CA)‡	−0.12**
Profile curvature (CA)‡	−0.14**
Slope degree (CA)‡	−0.16**
Slope percent (CA)‡	−0.16**
Contributing area	−0.10**
Relief (CA)‡	−0.04
Regression coefficients§	0.07

Regression coefficients between soil attributes and terrain attributes within selected sub-watersheds

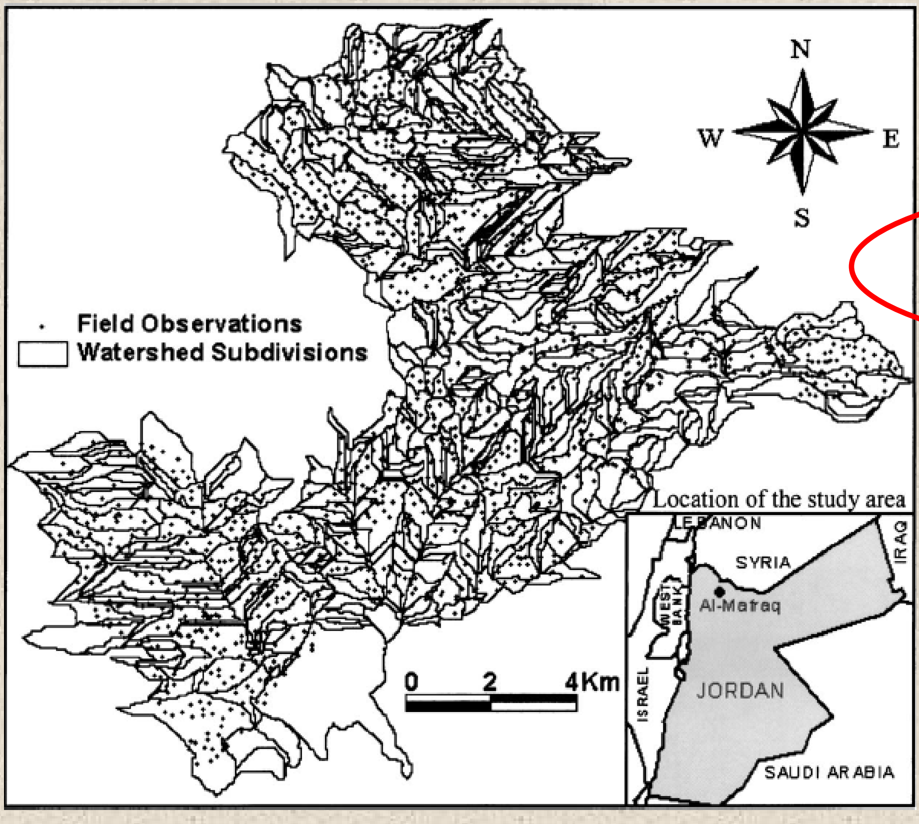
Rational: stream lines divided the watershed into two subdivisions

Each sub-division is constitutes of endless number of catena

Within each sub-division there is a unique relationship between soil and topography



Better regression coefficients between soil attributes and terrain attributes within selected sub-watersheds



Watershed number	No. of points	Soil depth
		cm
Watershed No. 300†	59	0.46
Watershed No. 300 Sub_1	28	0.54
Watershed No. 300 Sub_2	31	0.68
Watershed No. 112	45	0.41
Watershed No. 112 Sub_1	25	0.88
Watershed No. 112 Sub_2	20	0.86
Watershed No. 116	40	0.3
Watershed No. 116 Sub_1	21	0.84
Watershed No. 116 Sub_2	19	0.62
Watershed No. 102	45	0.27
Watershed No. 102 Sub_1	27	0.75
Watershed No. 269	34	0.33
Watershed No. 269 Sub_1	23	0.57
Watershed No. 386	38	0.28
Watershed No. 386 Sub_1	21	0.51

However, watershed subdivision was only serial number, cannot be extrapolated

Watershed subdivision were classified according to area and slope using unsupervised classification

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		cm
Watershed No. 300†	59	0.46
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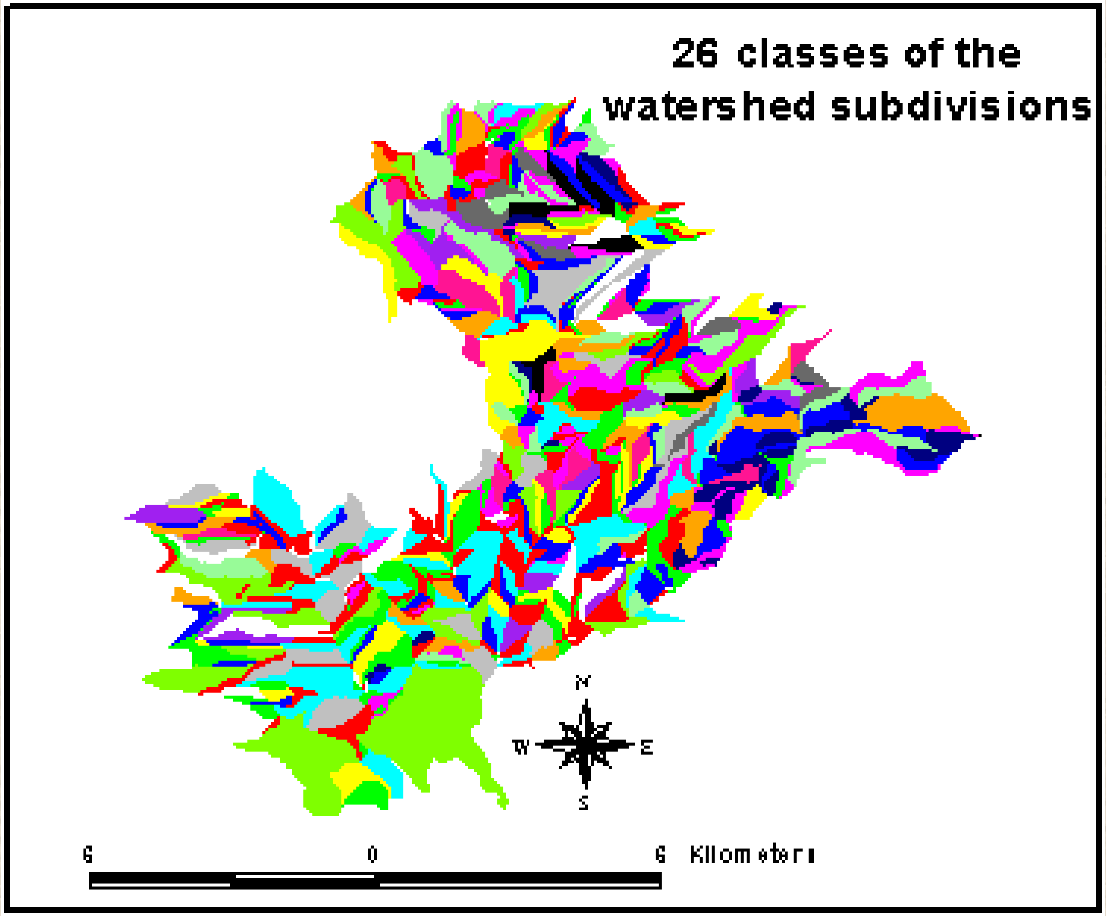
26 classes were optimum for this study area

highest regression coefficient between soil attributes and terrain attributes within each of the 26 classes

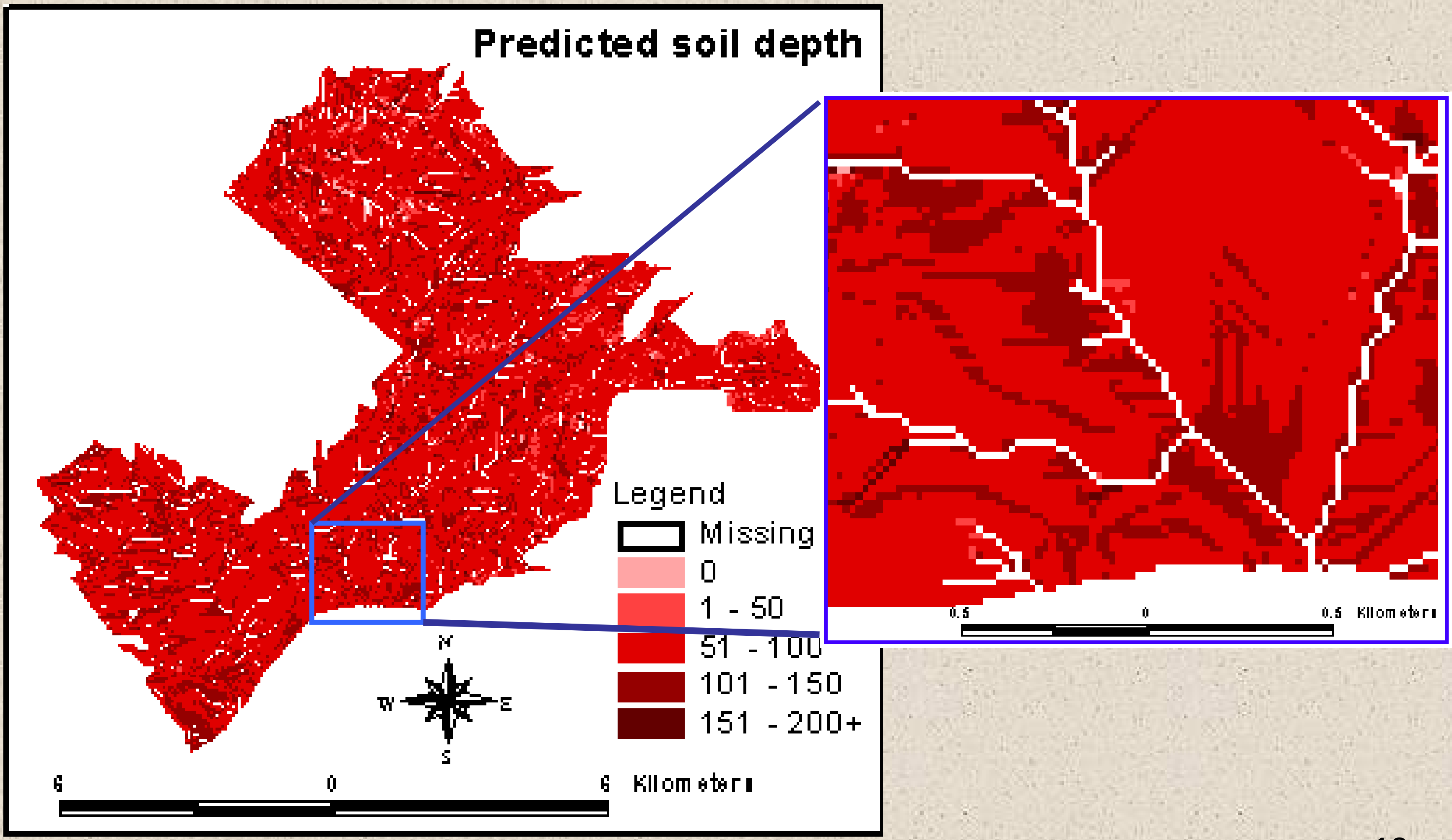


Linear models that utilize terrain attributes to predict soil attributes within each class were generated.

Example: Soil depth

	Model parameters						
Class no.	Constant	Slope percent	Curvature	Aspect	Contributing area	CTI	R^2
1	91.31	−20.69	1413.77	−1.63	−0.68	14.04	0.50
2	138.51	−21.07	199.44	−1.62	0.64	−9.24	0.42
3	75.21	6.42	−228.15	1.31	−0.66	3.81	0.04
4	108.47	−14.09	−1169.10	−0.84	0.46	−1.08	0.29
5	84.20	−1.22	−1058.66	2.73	0.26	−1.95	0.28
6	118.45	−16.92	360.98	−2.13	−0.59	−0.26	0.31
7	114.22	7.68	−227.30	−7.78	−1.06	2.87	0.32
8	99.17	−23.15	−488.15	2.94	2.08	−6.00	0.27
9	65.99	0.60	−160.83	1.88	0.30	−0.73	0.06
10	109.84	22.38	−810.89	−6.95	0.26	−7.22	0.25
11	89.11	1.00	−40.95	−4.65	−0.38	1.00	0.10
12	152.42	−29.10	−917.58	−0.80	0.60	−13.49	0.20
13	64.55	−12.06	41.60	3.95	0.02	10.30	0.17
14	115.15	3.44	−128.27	−2.02	0.71	−7.44	0.15
15	79.10	−10.40	−65.55	0.63	0.54	−0.86	0.15
16	134.95	−12.38	29.22	−5.46	0.53	−0.06	0.17
17	87.11	1.25	606.93	−0.46	0.66	0.23	0.17
18	84.76	−12.08	−456.99	0.27	1.65	−9.35	0.33
19	84.26	−10.55	−64.97	0.89	−0.17	2.73	0.06
20	106.43	−4.03	34.68	−2.20	0.04	−4.27	0.05
21	105.56	−12.22	−104.11	−1.68	−0.07	0.19	0.17
22	48.76	−3.57	−263.73	−0.38	−0.15	12.01	0.27
23	74.80	4.24	273.09	−1.22	−0.46	6.16	0.21
24	63.30	−4.56	189.39	0.41	−1.37	23.11	0.25
25	67.29	4.18	−30.50	−1.91	−2.41	18.12	0.33
26	78.98	−7.03	182.08	1.29	−0.12	6.48	0.17

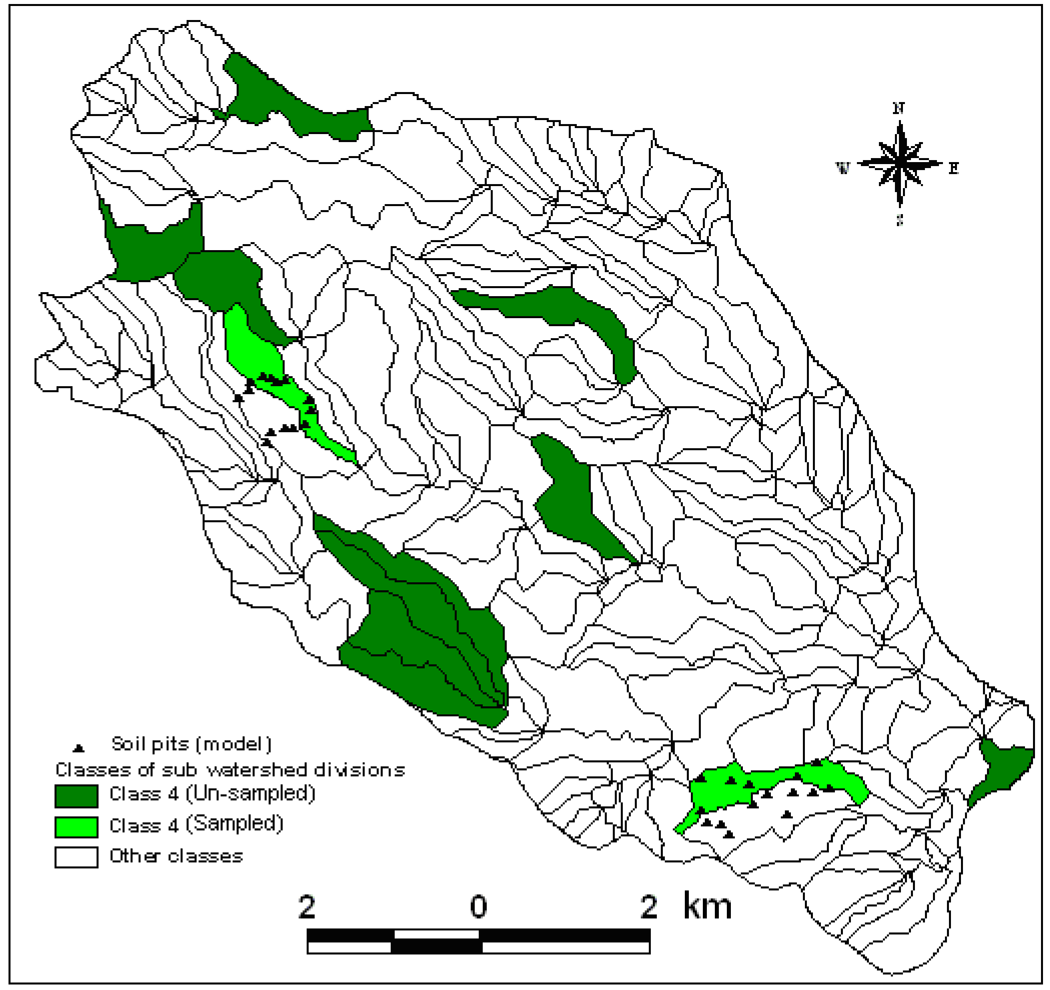
Regression models were applied for each class and predicted soil attributed were amalgamated for the whole study area.



Accuracy of prediction

Soil Attribute	Confidence of Prediction	Prediction Accuracy
Erosion type	± One class	48.4%
Water holding capacity	± 50 mm/cm	75.8%
Surface cover percent	± 10 %	78.7%
Soil depth	± 50 cm	89.3%
Soil texture	± One class	90.3%
Surface cover type	± One class	94.5%
Erosion class	± One class	98.0%

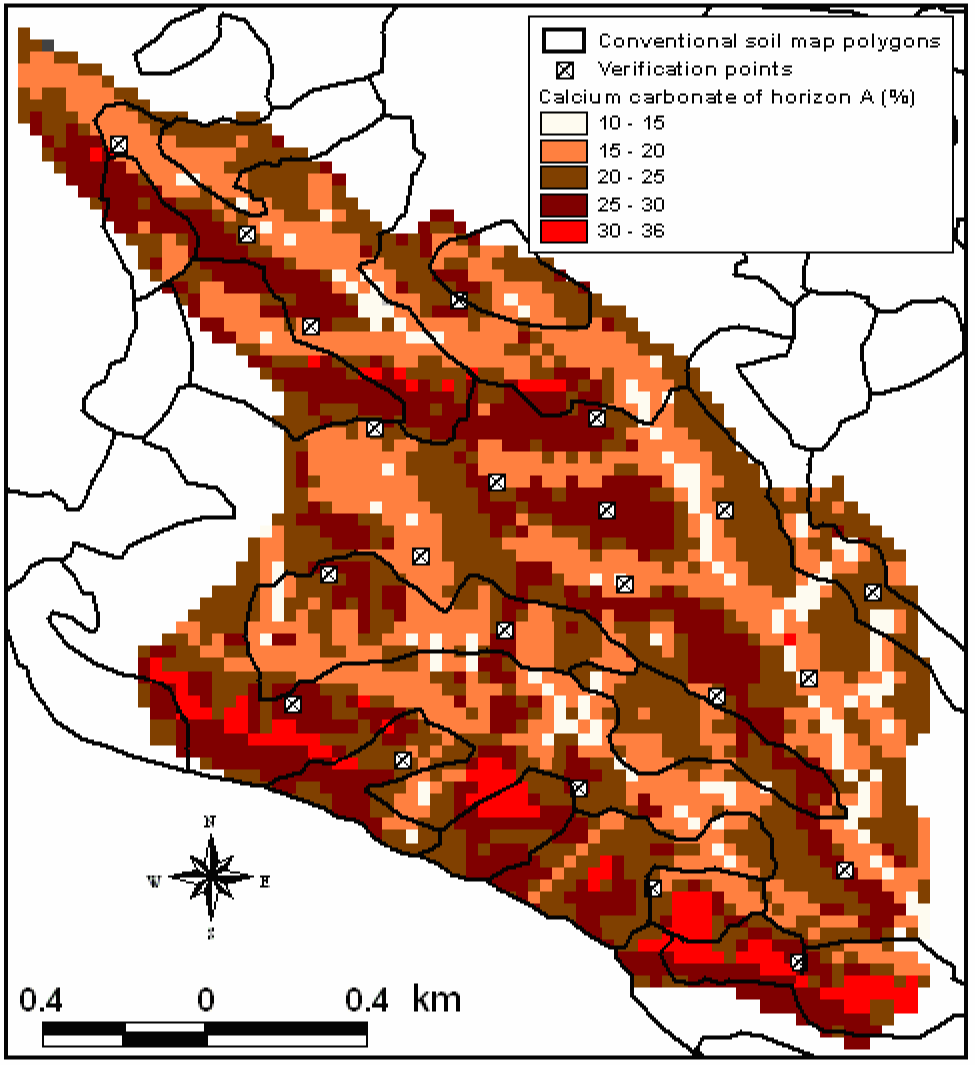
The prediction model was applied for other study area to predict surface and sub-surface soil properties with good results even for un-sampled watershed subdivisions



Root mean square error (RMSE) of the predicted soil characteristics was generally better than those derived from traditional soil map (scale 1:5,000)

Soil variables	RMSE Prediction	RMSE Soil map	Soil variables	RMSE Prediction	RMSE Soil map
Carbonate % A[(a)]	3.4	8.6	Silt % A	13.5	10.6
Carbonate % B[(a)]	10.5	16.0	Silt % B	24.5	23.1
Organic Matter % A	0.5	0.4	Clay % A	7.1	12.8
Organic Matter % B	0.4	0.4	Clay % B	24.1	30.4
pH A	0.3	0.7	Depth (cm) A	6.4	11.0
pH B	3.4	3.8	Depth (cm) B	35.5	53.3
EC (dS/m) A	0.3	0.4	Soil Depth (cm)	33.5	56.8
EC (dS/m) B	0.8	1.4	No .of horizons	1.1	1.4
Bulk Density (g cm^{-3}) A	0.2	0.2	Stone % A	10.8	12.6
Bulk Density (g cm^{-3}) B	0.6	0.7	Stone % B	20.8	11.1
Sand % A	14.1	18.2	Surface stone %	13.1	23.2
Sand% B	8.7	12.2			

Spatial distribution of the predicted soil characteristic (carbonate content of horizon A) is better than those of the traditional soil map

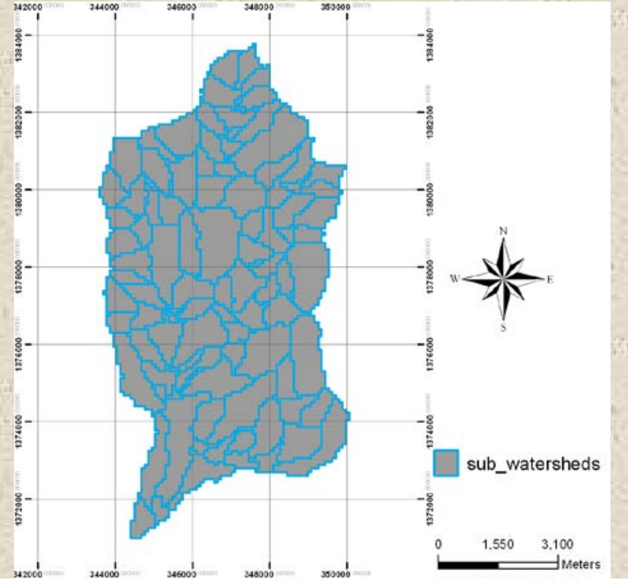


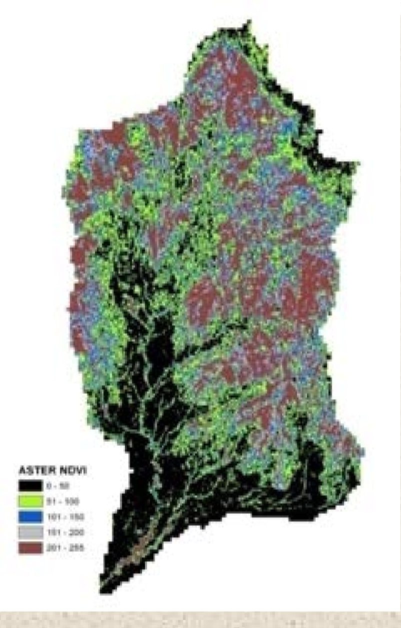
Application in Ethiopia

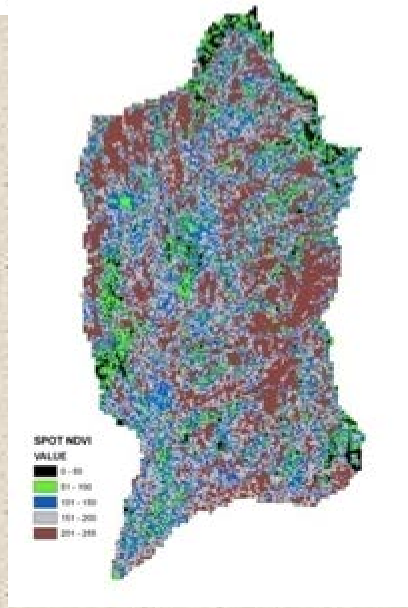
Using SRTM 90m

NDVI from ASTER images
At two different dates

180 observations used for
Prediction and 40 for
Accuracy assessment







Acceptable results given the availability of input data at Global level

Root mean square errors between field observations and predicted soil attributes

Predicted soil attributes	RMSE	
Soil depth	26.4	cm
Clay percent	12.6	%
Silt percent	7.3	%
Sand percent	9.4	%
Organic matter	1.39	%
Bulk density	0.18	g/cm^3
pH	0.38	
Total Nitrogen	0.29	%
Exchangeable Phosphorus	19.41	ppm
Stone cover soil surface	12.2	%
Stone in the soil	12.4	%

However, number of observations used is 180 for 60 sq. Km area

Testing accuracy using few observations to optimize field work required

Percent of observations predicted correctly within ± 50 cm range from field observed soil depth values

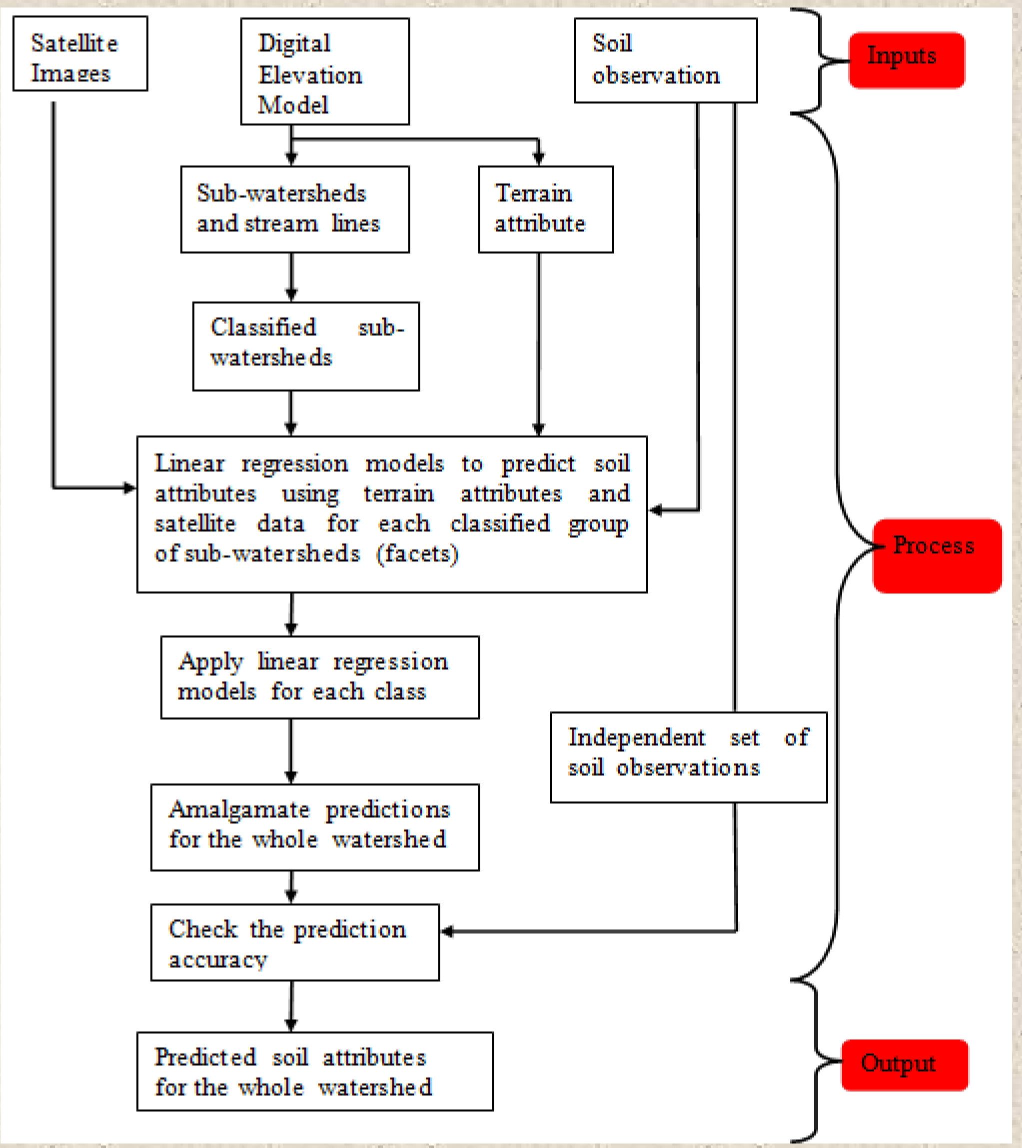
No. of observations used	Percent of predicted observations (%)
180	97.5
150	95
120	92.5
90	87.5
60	87.5
40	72.5
30	67.5
25	65
20	35

Future

Design user-friendly toolkit to predict soil attributes :

- Stand alone
- Sub-model within SWAT

Encourage applications at various levels and purposes

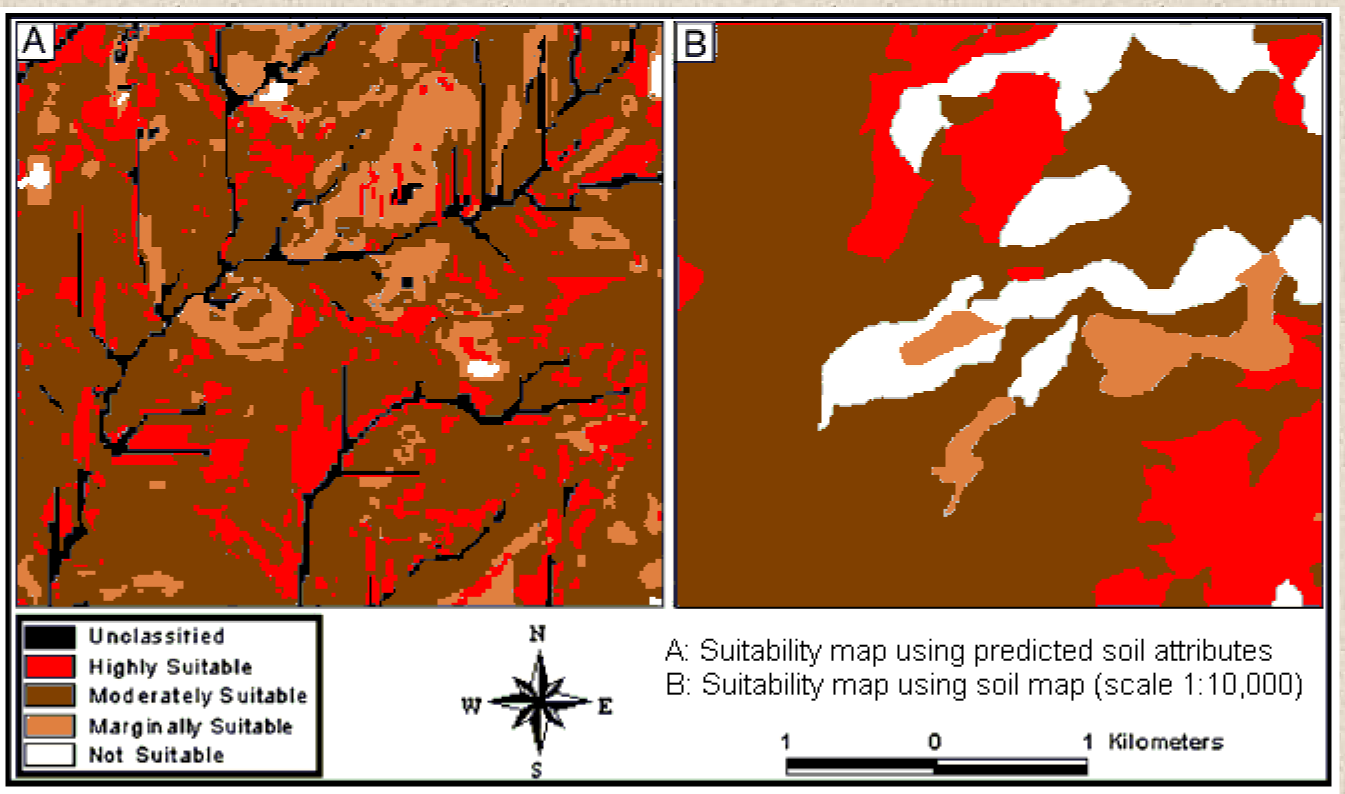


Example of application: suitability analysis

The accuracy of the suitability classification derived from predicted soil attributes is comparable with the accuracy of classifications derived from traditional 1:10,000 soil maps (for range crops)

Points Suitability	Level 3 soil map				Level 2 soil map				Prediction model			
	S1	S2	S3	NS	S1	S2	S3	NS	S1	S2	S3	NS
S1	**1395**	47	19	0	**1361**	19	0	0	**1359**	0	6	0
S2	57	**93**	6	0	144	**12**	0	0	98	**55**	3	0
S3	20	25	**7**	0	49	3	0	0	34	18	**0**	0
NS	0	0	0	0	0	0	0	0	0	0	0	**0**
Total Agreement		**89.6**				**82.3**				**84.7**		

The spatial distribution of the suitability classification derived from the predicted soil attributes indicated more realistic pattern



Concluding remarks

Modelling of the soil-landscape relationships within small watershed subdivisions is a promising approach to predict soil attributes for large areas.

The spatial distribution of the predicted soil attributes is provided in more detailed form than what the soil map provides.

Concluding remarks

The accuracy and spatial distribution of the suitability classification derived from predicted soil attributes compares favourably with those derived from traditional soil maps.

The digital output is an advantage that facilitates the incorporation into modern modelling techniques at various scales.

Thank You …