Soil-landscape modeling to predict the spatial distribution of soil attributes for environmental applications

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Content

Motivation .. Why predicting soil attributes

Rational for new program

Structure of the program

Applications

Future …

Soil Survey Data

Limitation of soil maps:

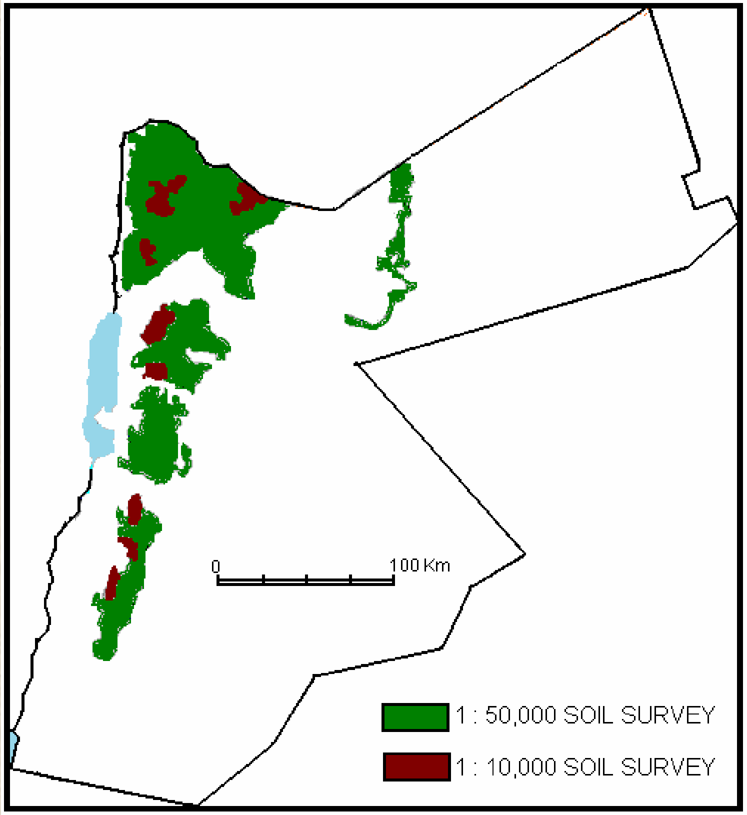
The coverage, especially with enough details, in dry areas is usually limited. The cost of extending this coverage is high.

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

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

ALTERNATIVE SOURCES OF SOIL INFORMATION

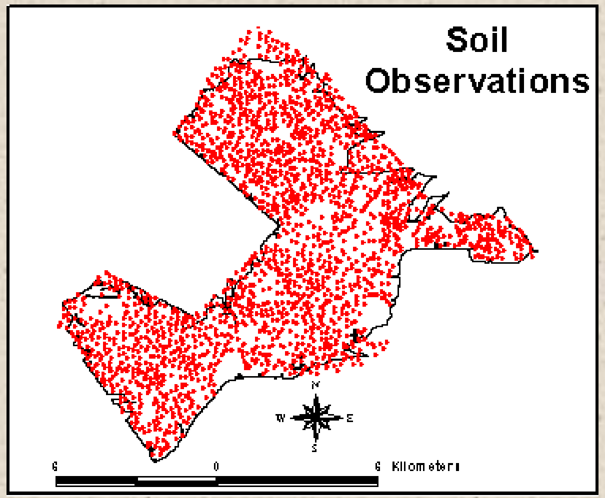
Prediction of soil attributes using terrain attributes

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

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

Significant but low correlation

Low regression coefficients



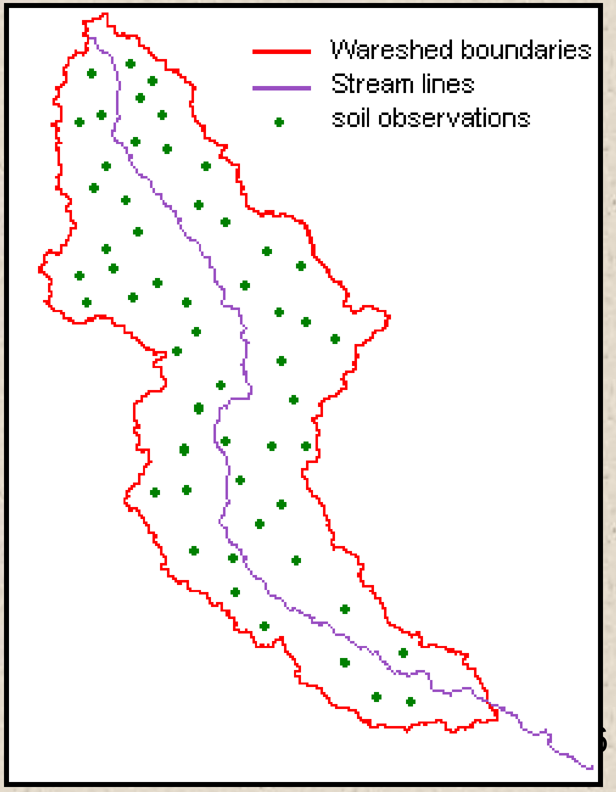
Statistical interpolation

Better 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

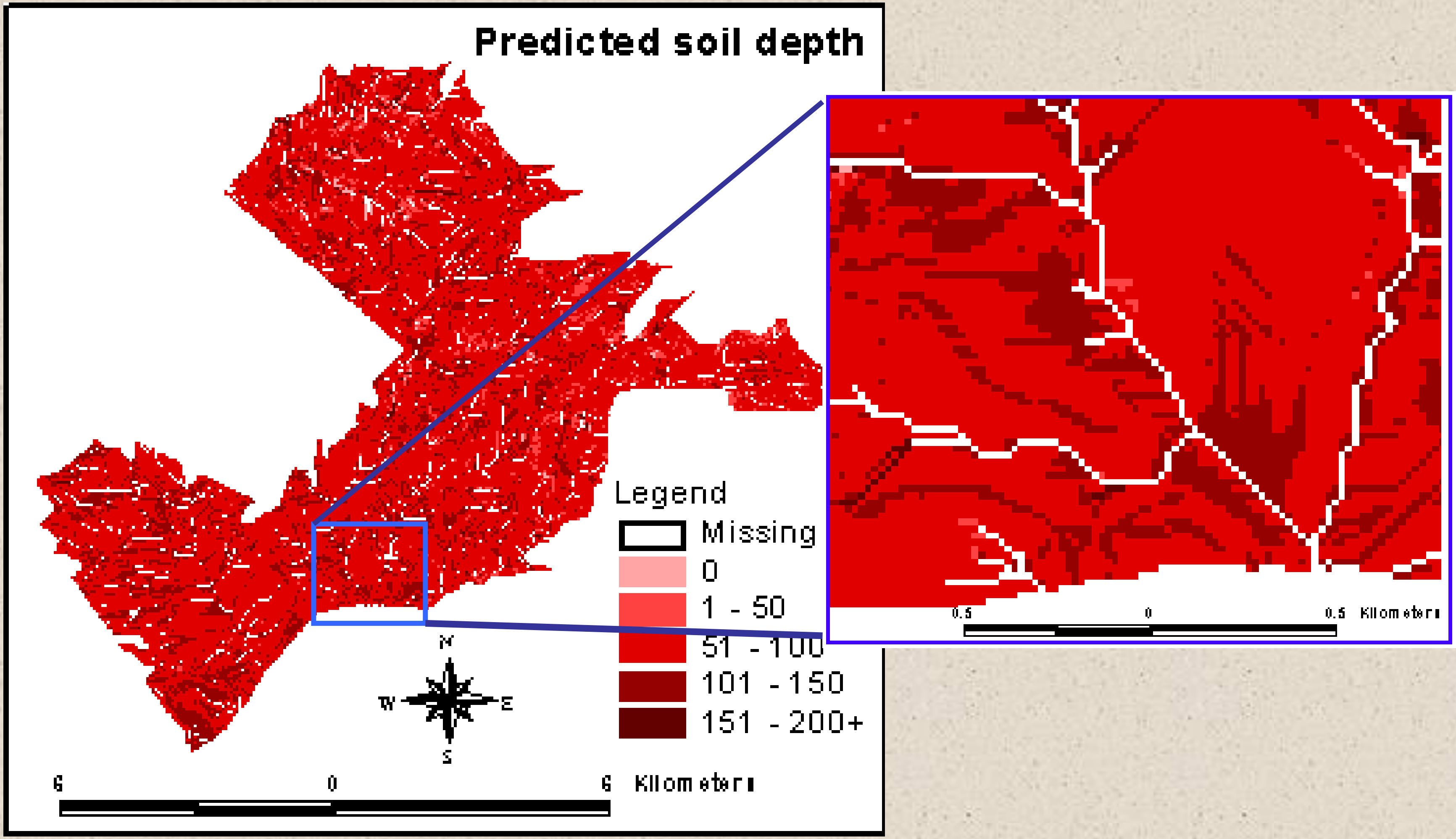


Linear models that utilize terrain attributes to predict soil attributes within each class are generated

Example: Soil depth

Class no.	Constant	Slope percent	Curvature	Aspect	Contributing area	CTI	R^2
	Model parameters						
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 are applied for each class and predicted soil attributed are generated for the whole study area

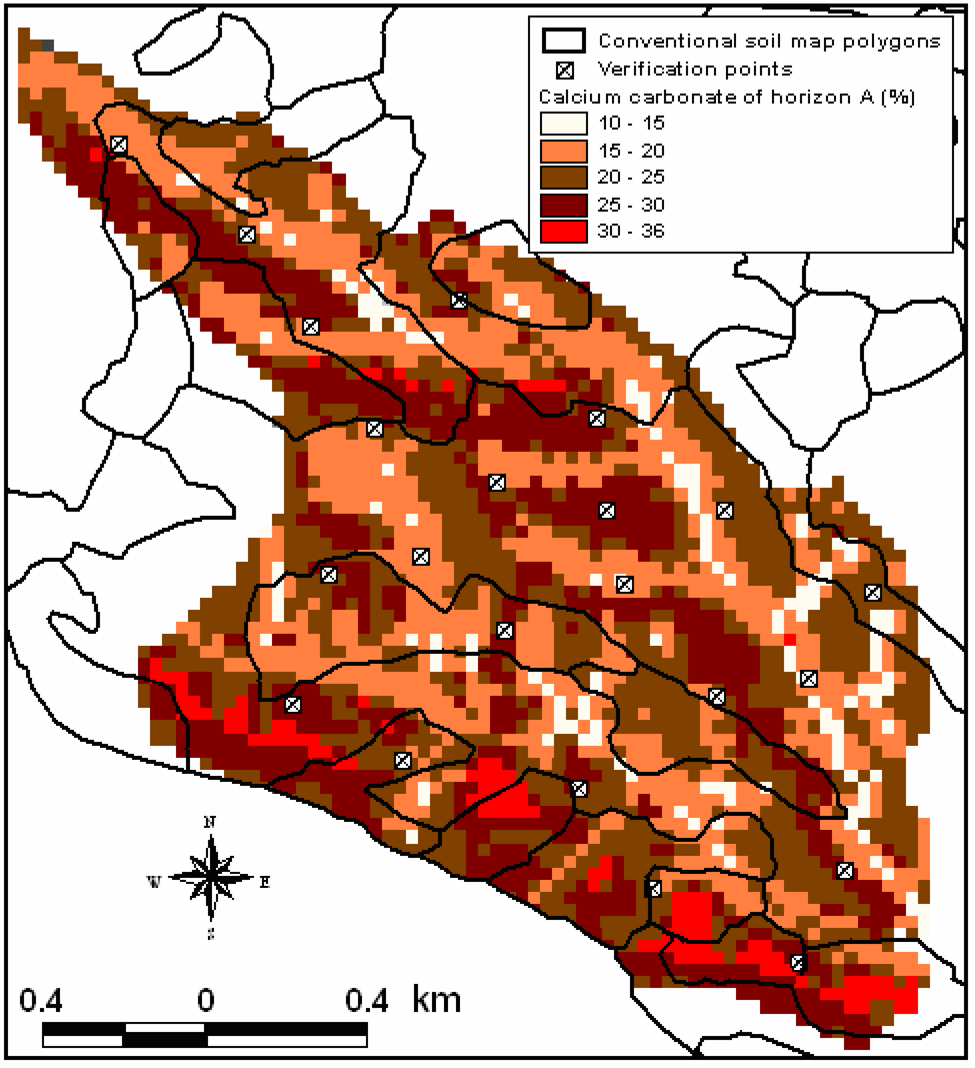


Accuracy of the predicted soil characteristics was generally comparable with those derived from traditional soil map (scale 1:5,000)

Chemical, physical, and soil fertility related attributes for the surface and sub-surface soils

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 is better than those of the traditional soil map

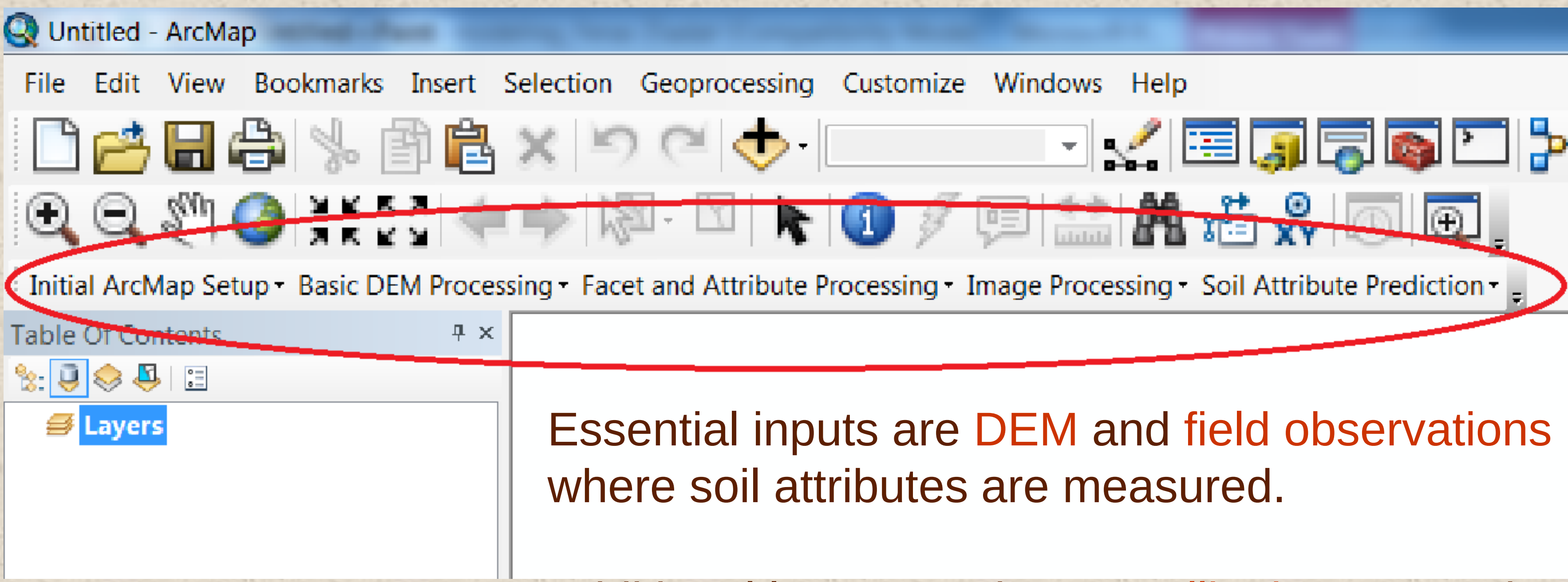


Structure of the program

User-friendly toolkit to predict soil attributes:

Stand alone OR Sub-model within SWAT

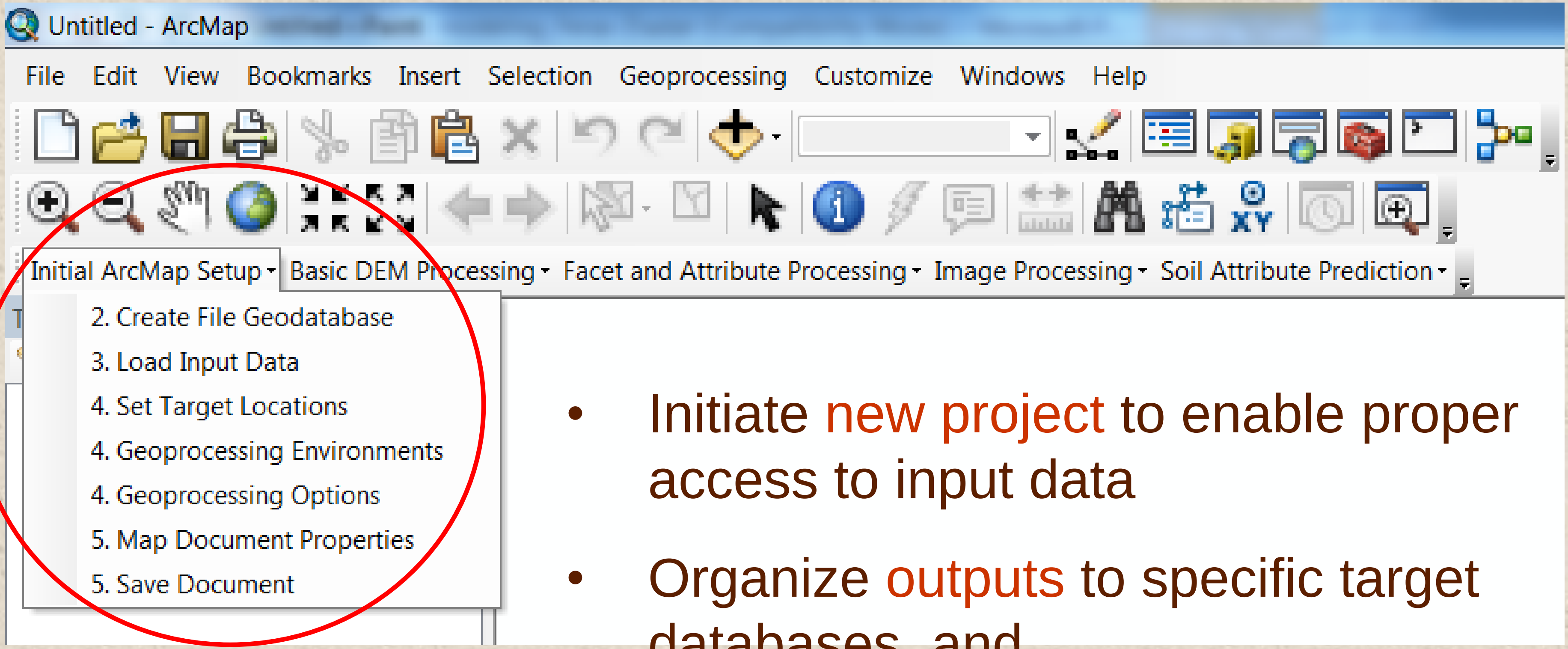
SLEEP – Soil-Landscape Estimation and Evaluation Program



Essential inputs are DEM and field observations where soil attributes are measured.

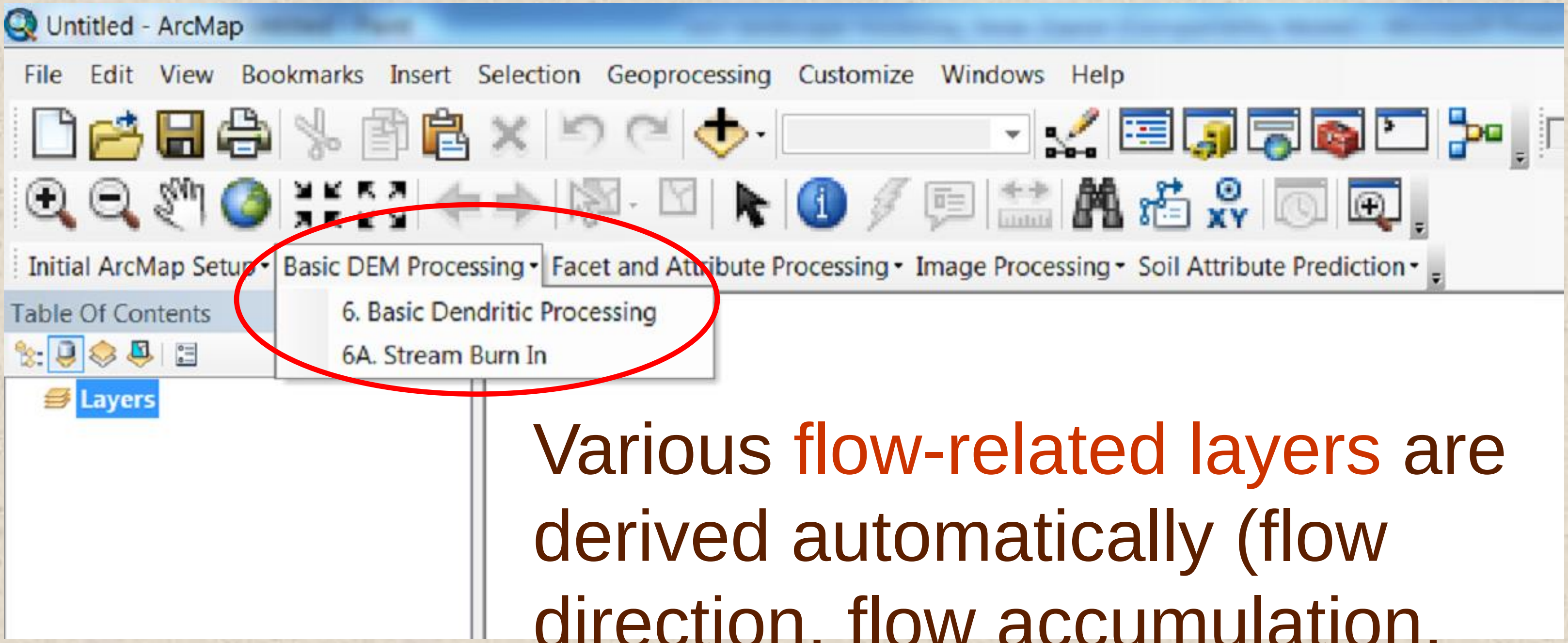
Additional layers, such as satellite images and auxiliary data, improve the prediction accuracy.

Initial ArcMap Setup



- Initiate new project to enable proper access to input data
- Organize outputs to specific target databases, and
- Avoid duplication of files in case of running many iterations

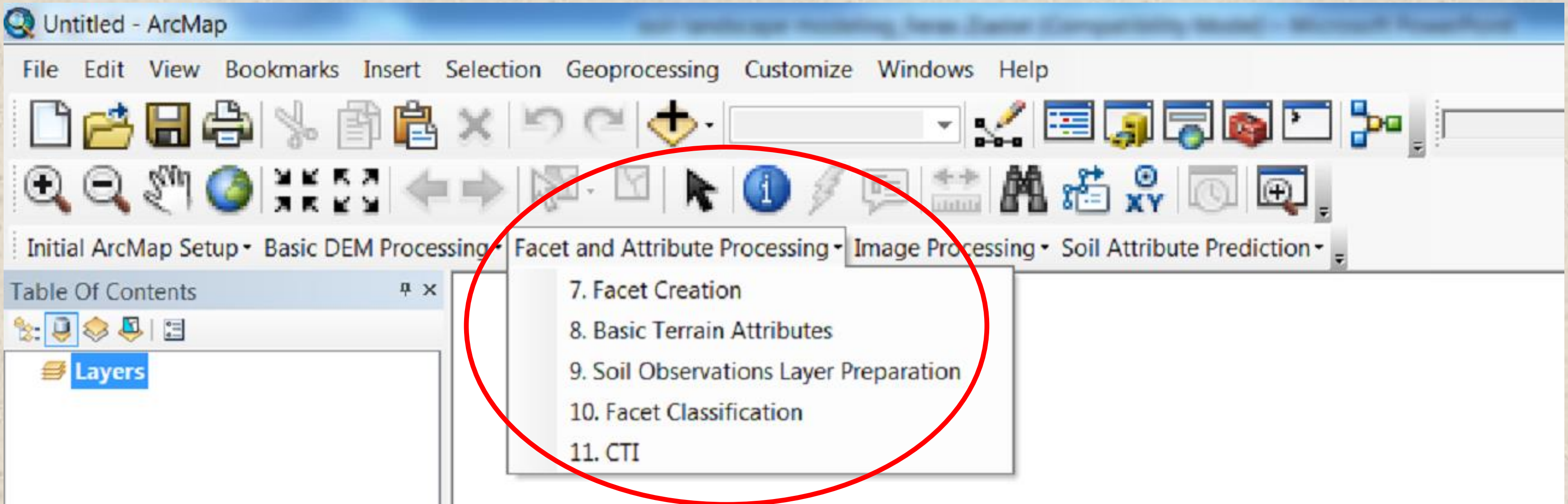
Basic DEM Processing



Various flow-related layers are derived automatically (flow direction, flow accumulation, stream line, sub-watersheds within whole watershed and others).

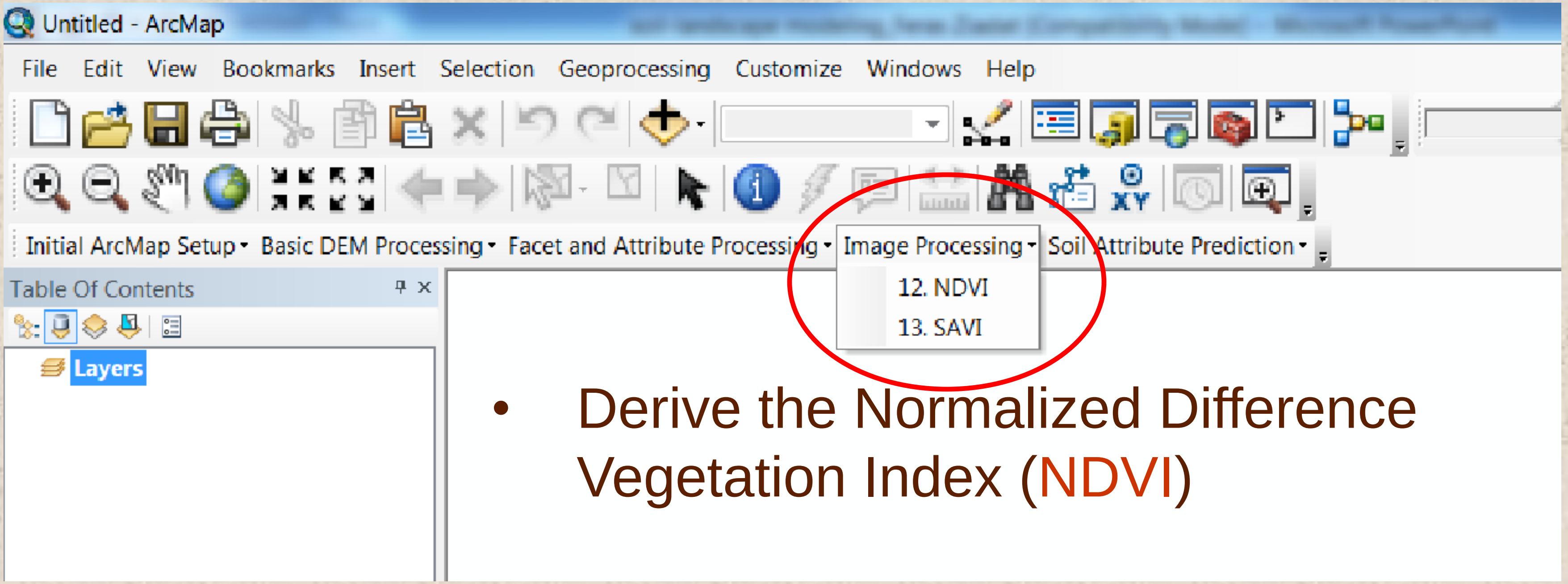
Stream burn in if many sinks exist

Facet and Attribute Processing



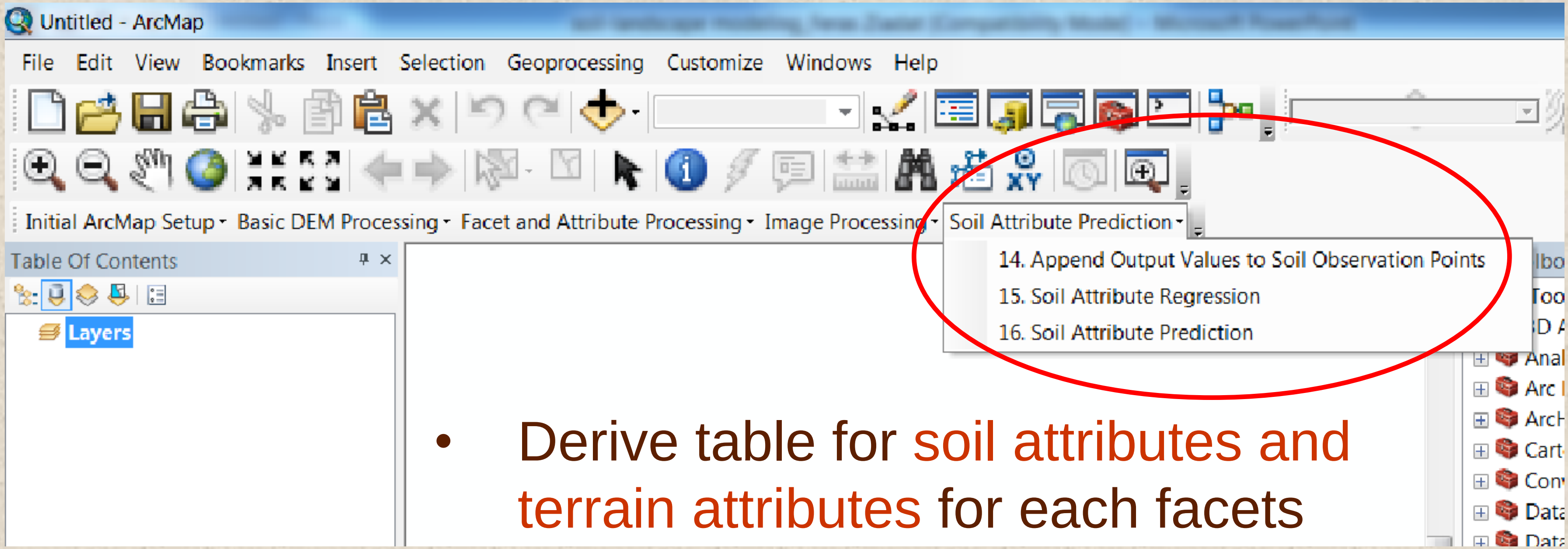
- Subdivide sub-watersheds into facets and facets classification
- Derive terrain attributes
- Prepare soil (field) observation layer
- Derive compound Topographic Index CTI

Image Processing



- Derive the Normalized Difference Vegetation Index (NDVI)
- Derive the Soil Adjusted Vegetation Index (SAVI)
- Derive any other indices and/or ancillary layers

Soil Attribute Prediction



- Derive table for soil attributes and terrain attributes for each facets class
- Establish regression models to predict soil attributes
- Apply regression models to predict soil attributes for each pixel

Application in Ethiopia

Using SRTM 90m

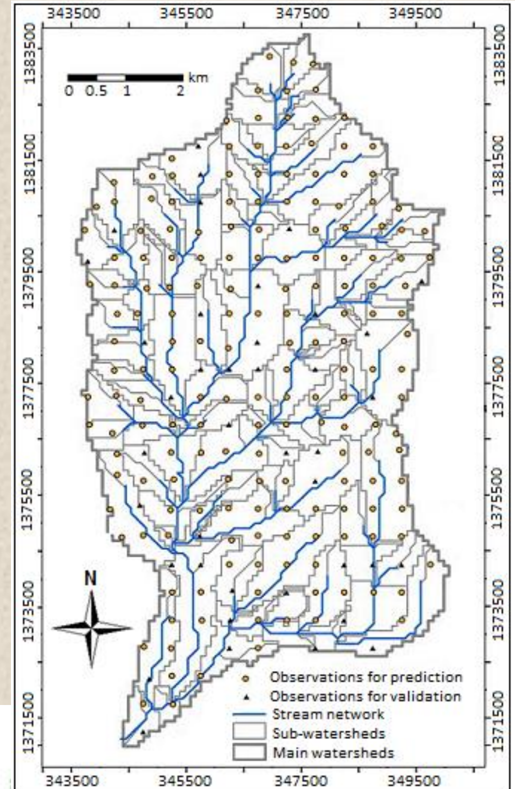
NDVI from ASTER images

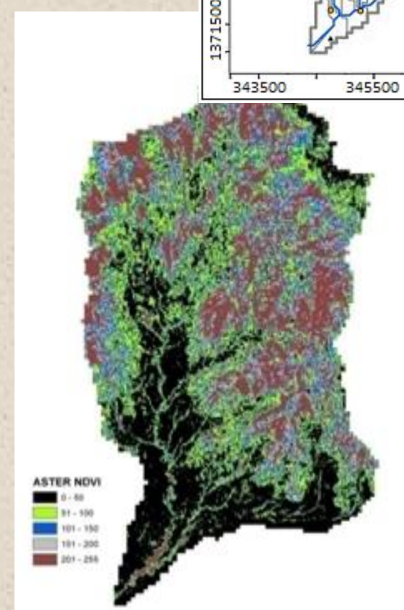
At two different dates

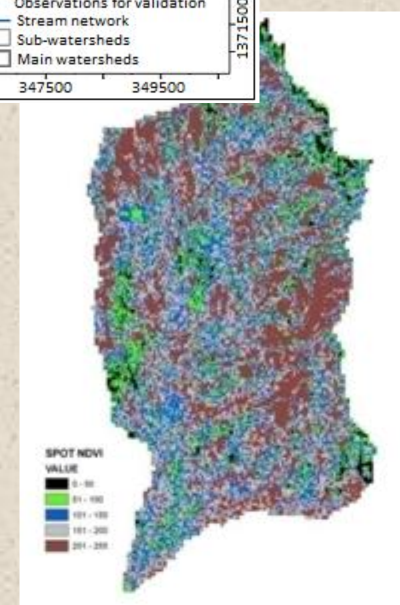
180 observations used for

Prediction and 40 for

Accuracy assessment







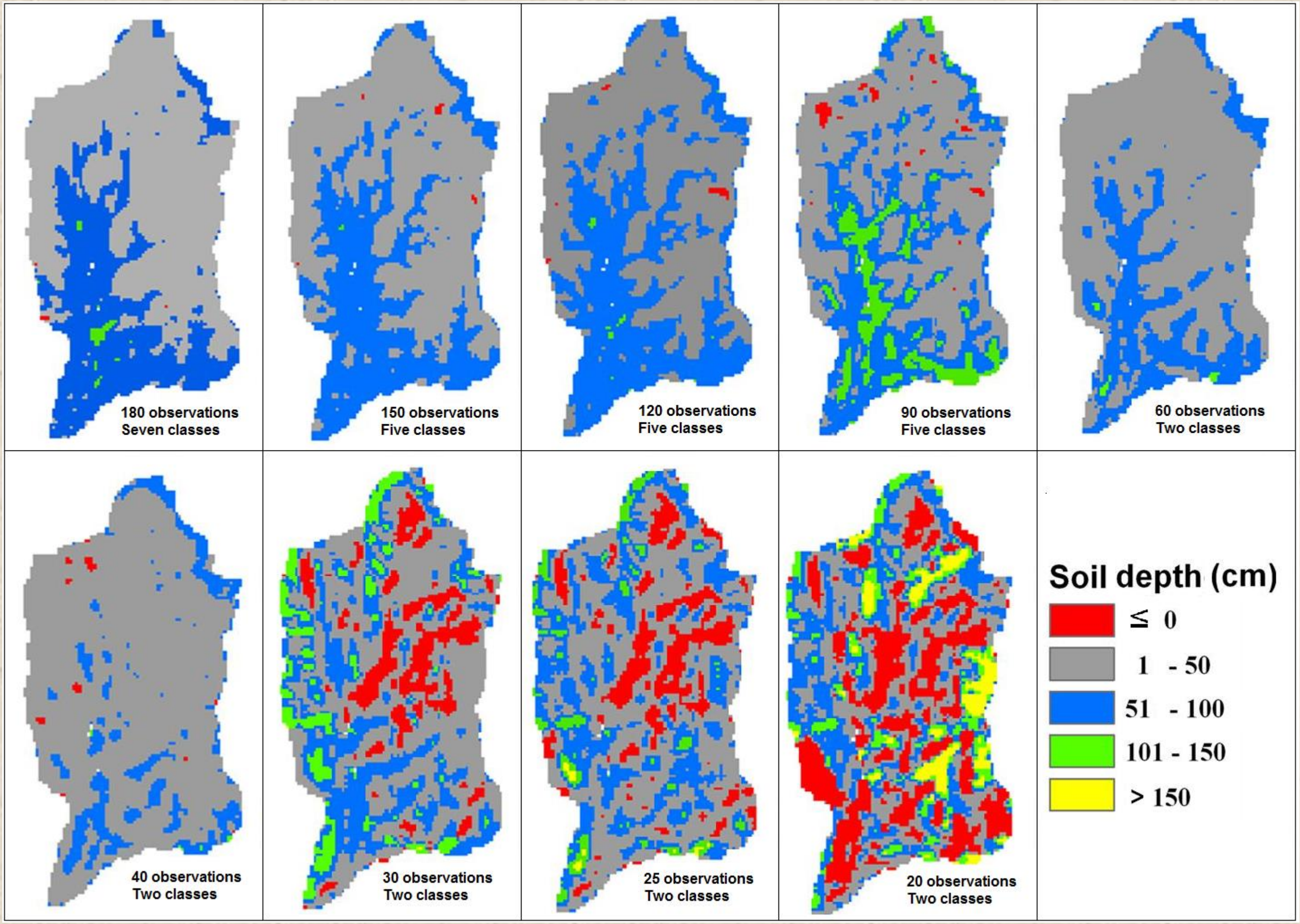
Testing accuracy using few observations to minimize the field work and maintain accuracy

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

Watershed area ~ 60 sq. km

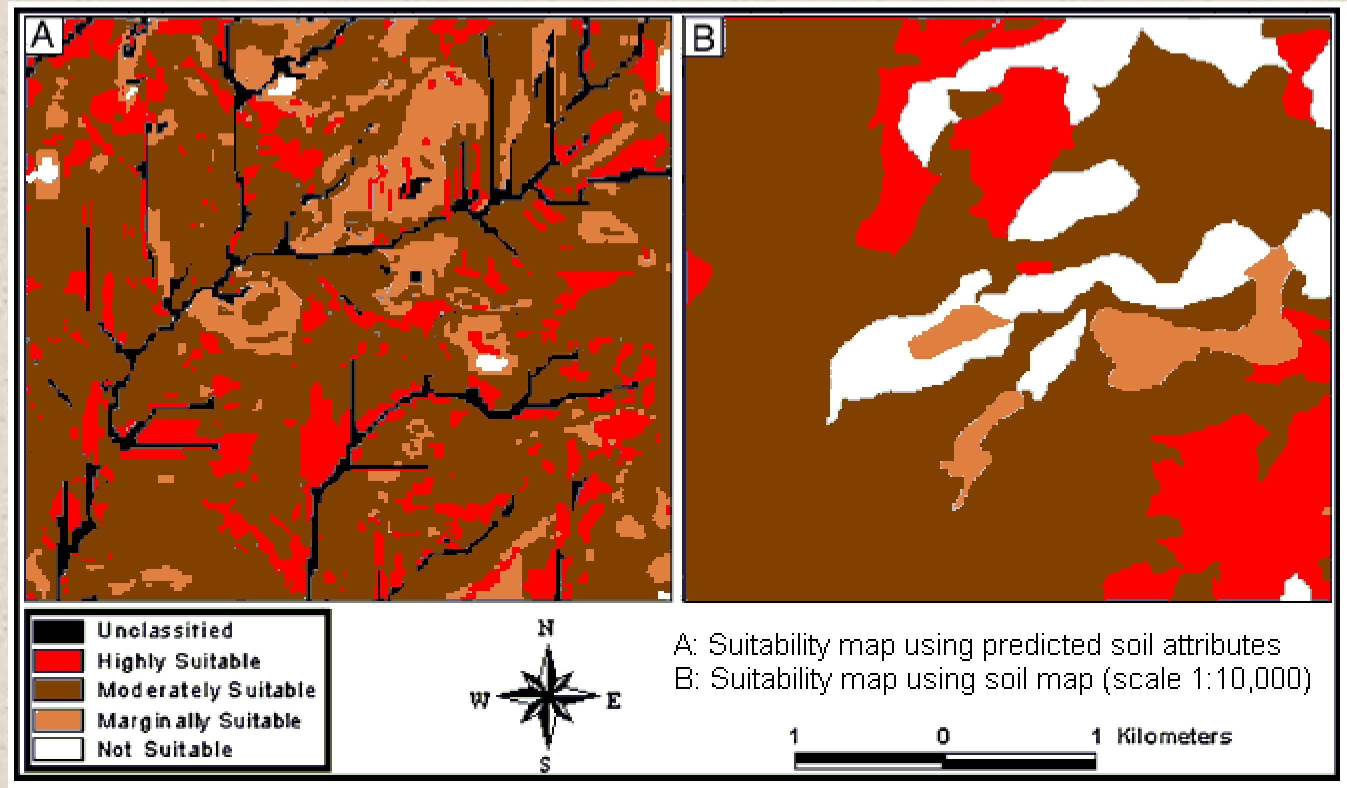
Prediction of soil depth using different number of observations



Example of application: suitability analysis

Accuracy of the suitability classification derived from predicted soil attributes is comparable with those derived from traditional 1:10,000 soil maps

Spatial distribution of suitability classes derived from the predicted soil attributes indicated more realistic pattern



Future …

Launch the program with documentation and help package

Encourage applications at various levels and purposes with minimum input from the field

Example: compare SLEEP predicted soil attributes with statistical interpolation and soil maps on the performance of SWAT in Ethiopia

Continuous development of the program …

Thank You …