The Legacy of Soil Mapping in Nigeria:

From analogue to digital soil mapping

FACULTY OF
AGRICULTURE
AND ENVIRONMENT

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Outline

- Introduction
  - A bit about Digital Soil Mapping (DSM) and GlobalSoilMap.Net
- Where is Nigeria and Why Nigeria?
- Historical (analogue) soil mapping in Nigeria
- Preliminary results of recent effort towards DSM for Nigeria
- Future work

Global Digital Soil Mapping- the Motivation

GlobalSoilMap.net: A global digital soil mapping initiative

Global Digital Soil Mapping- the Motivation

GlobalSoilMap.net project

- was initiated in 2008 with a major funding from Melinda/Bill Gate Foundation; it aims to:
  - produce spatial predictions of key soil properties at continuous depth intervals at a spatial resolution of 100 m for the entire world
  - derive management recommendation to the stakeholders
  - link the GSM.net information to the end-user through cyberinfrastructure

Global Digital Soil Mapping

The continuous depth intervals

- Are 0-5, 5-15, 15-30, 30-60, 60-100, 100-200 cm
- Are estimated by a spline function to compensate for missing soil horizons and incompatible horizon depths
- Are then populated to 100-m resolution across the landscape

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Global Digital Soil Mapping- the Motivation

GlobalSoilMap.net project (now its second phase in development)

- Has several nodes across the globe
- Has an African node based at CIAT- Nairobi Kenya
  - The West African sub-node (including Nigeria) is based in Mali
- Involves the collection and use of legacy soil data and/or contemporary data
- Also involves covariate data that are easier to acquire than the measurement of soil attributes

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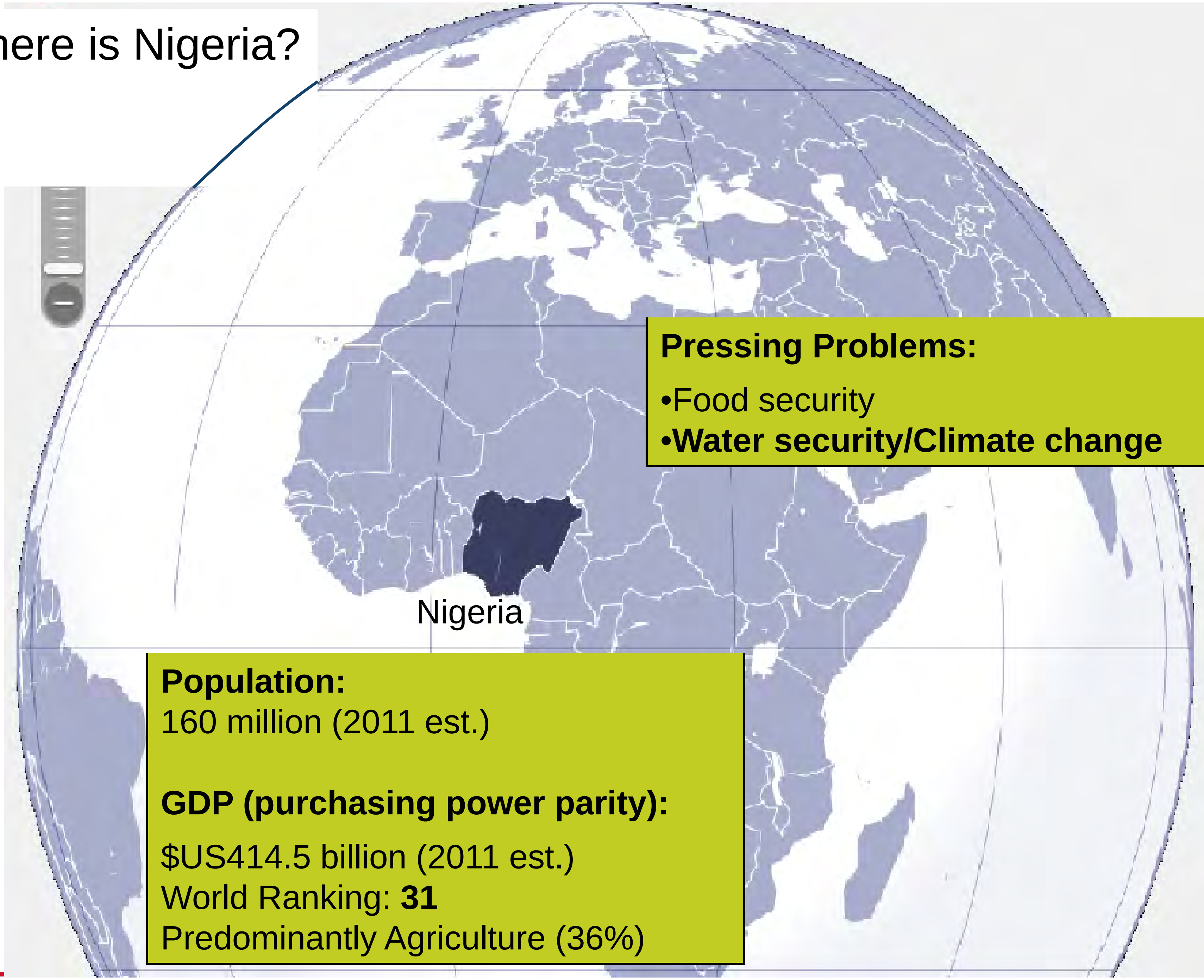
Where is Nigeria and Why Nigeria?

Where is Nigeria?



Pressing Problems:

- Food security
- **Water security/Climate change**

Population:
160 million (2011 est.)

GDP (purchasing power parity):

$US414.5 billion (2011 est.)
World Ranking: **31**
Predominantly Agriculture (36%)

Where is Nigeria?

Where is Nigeria?

The origin of me

I was from here:
Village serenity or less chaos than Lagos?

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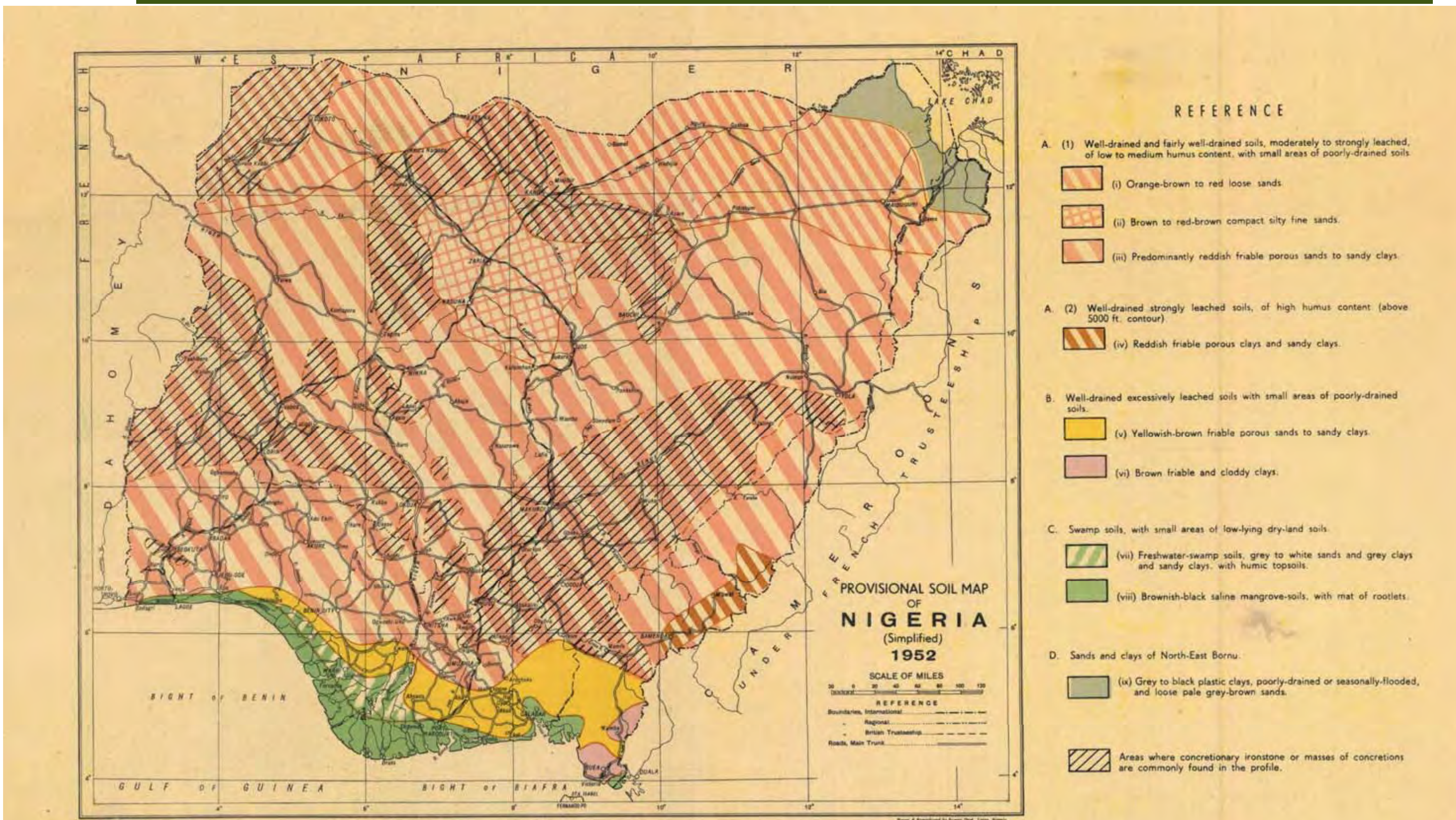
Why are Legacy Soil Data Useful for DSM for Nigeria?

Why Legacy Soil Data are Important for DSM

- Soil legacy data have a major role to play in DSM, especially in digital soil data-poor countries such as Nigeria
- In many of such countries, legacy soil surveys (since the colonial period) would probably be the main sources of data for DSM
- Although some of these survey reports/maps have been captured/catalogued, more are gathering dusts in various institutions
- We need to capture and transform them for DSM

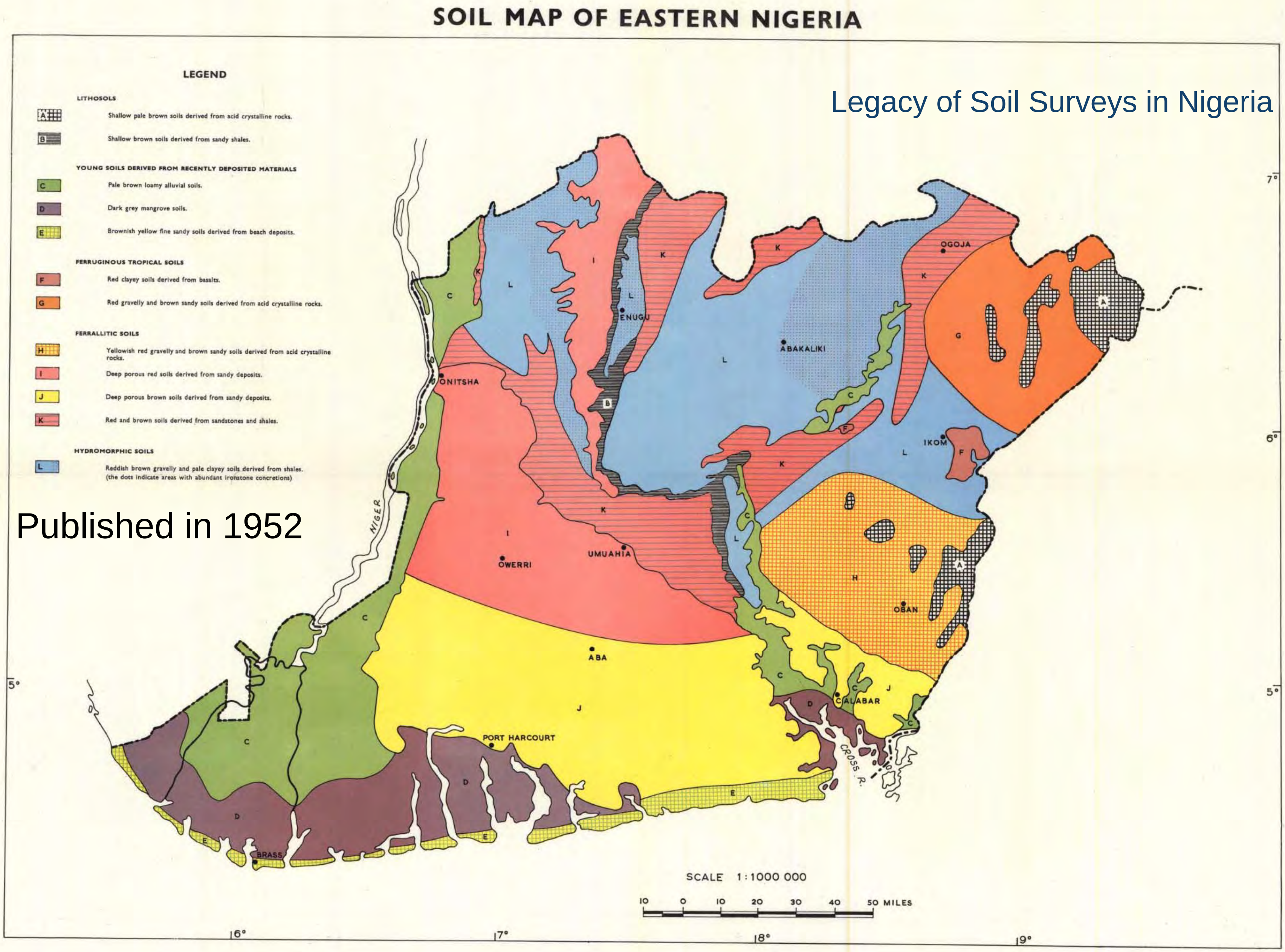
The History of Soil Mapping in Nigeria

Legacy of Soil Surveys in Nigeria



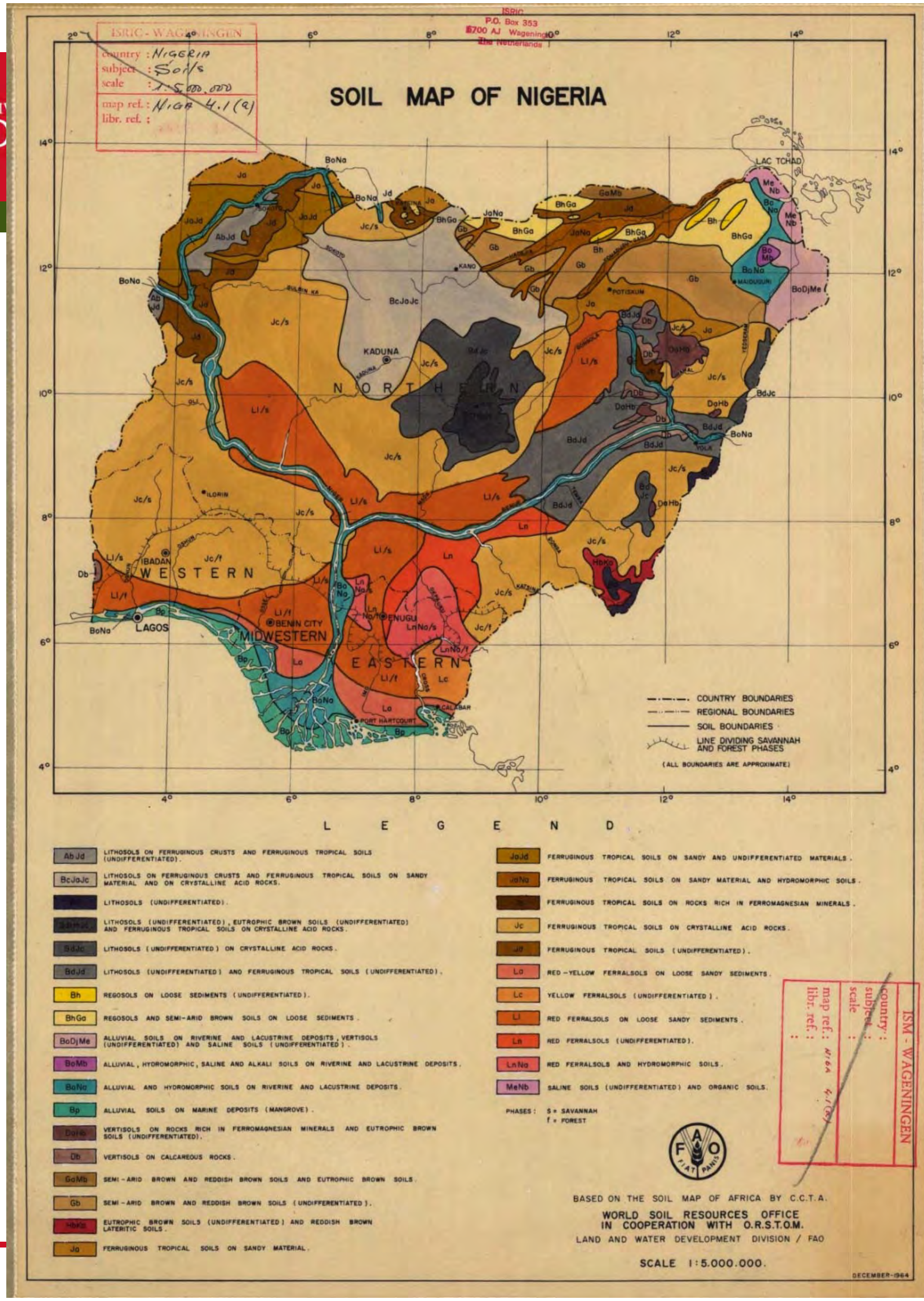
Provisional Soil Map of Nigeria- Published in 1952

Legacy of Soil Surveys in Nigeria

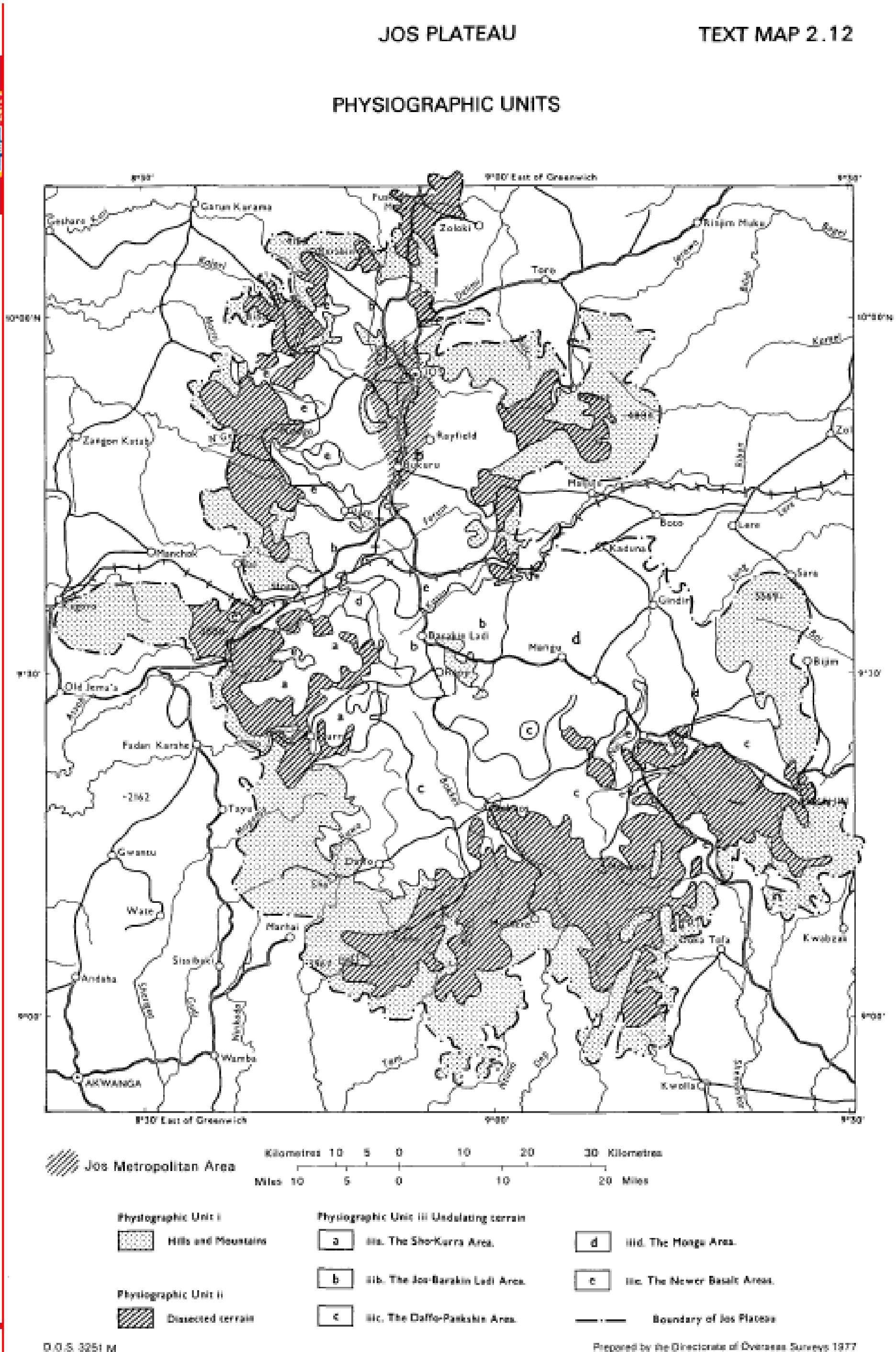


Published in 1952

Legacy of Soil Surveys in Nigeria



- Soil Map based on CCTA map of Africa, Published by FAO's Land Division in 1964; Scale: 1:5M
- The precursor of the current "Digital Soil Map" of the World



Legacy of Soil Surveys in Nigeria

- Physiographic Map of Jos Plateau
- Published by British owned Land Resource Division of the Overseas Development Administration in 1976
- Land system approach, with each physiographic unit having a representative profile (data)

Legacy of Soil Surveys in Nigeria

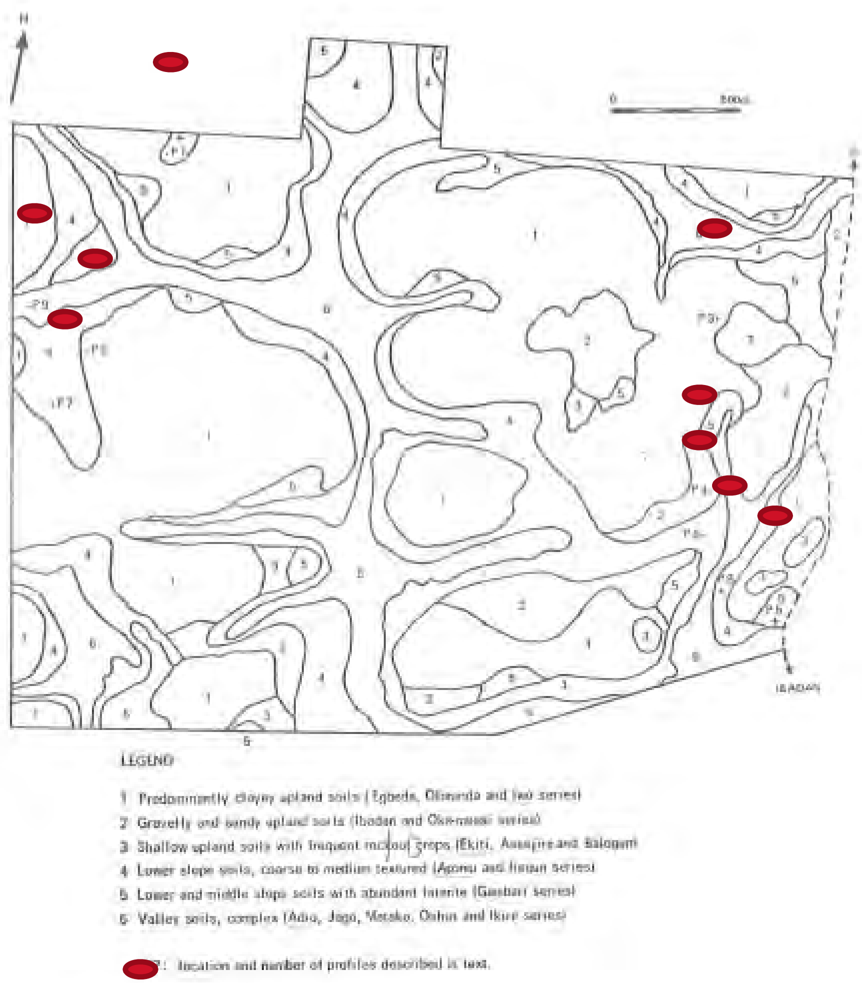
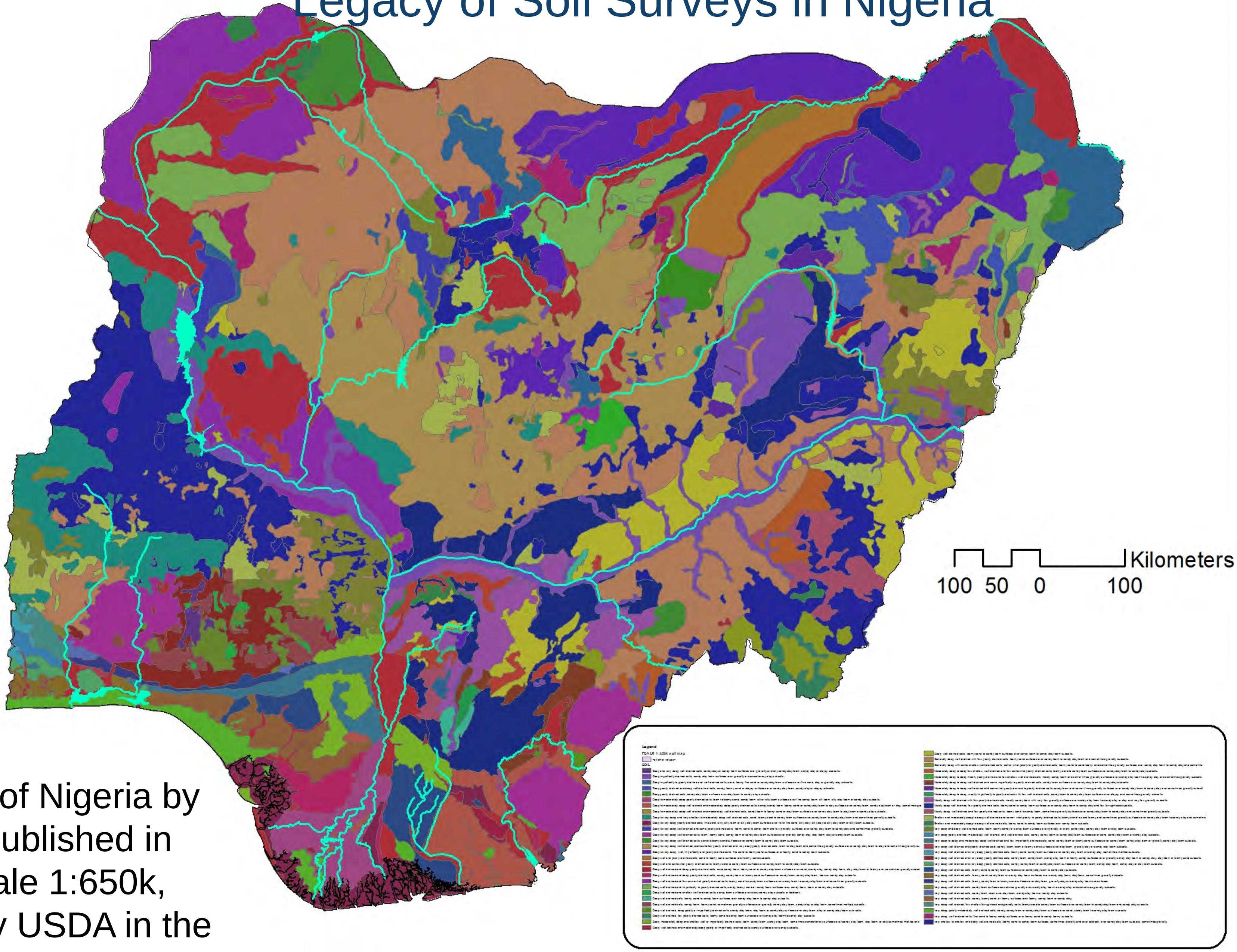


Fig. 1. Simplified soil map of IITA.

Farm-level (detailed) Soil Map of International Institute for Tropical Agriculture (IITA)- at a scale of 1:25,000, with detailed profile description and data

Legacy of Soil Surveys in Nigeria



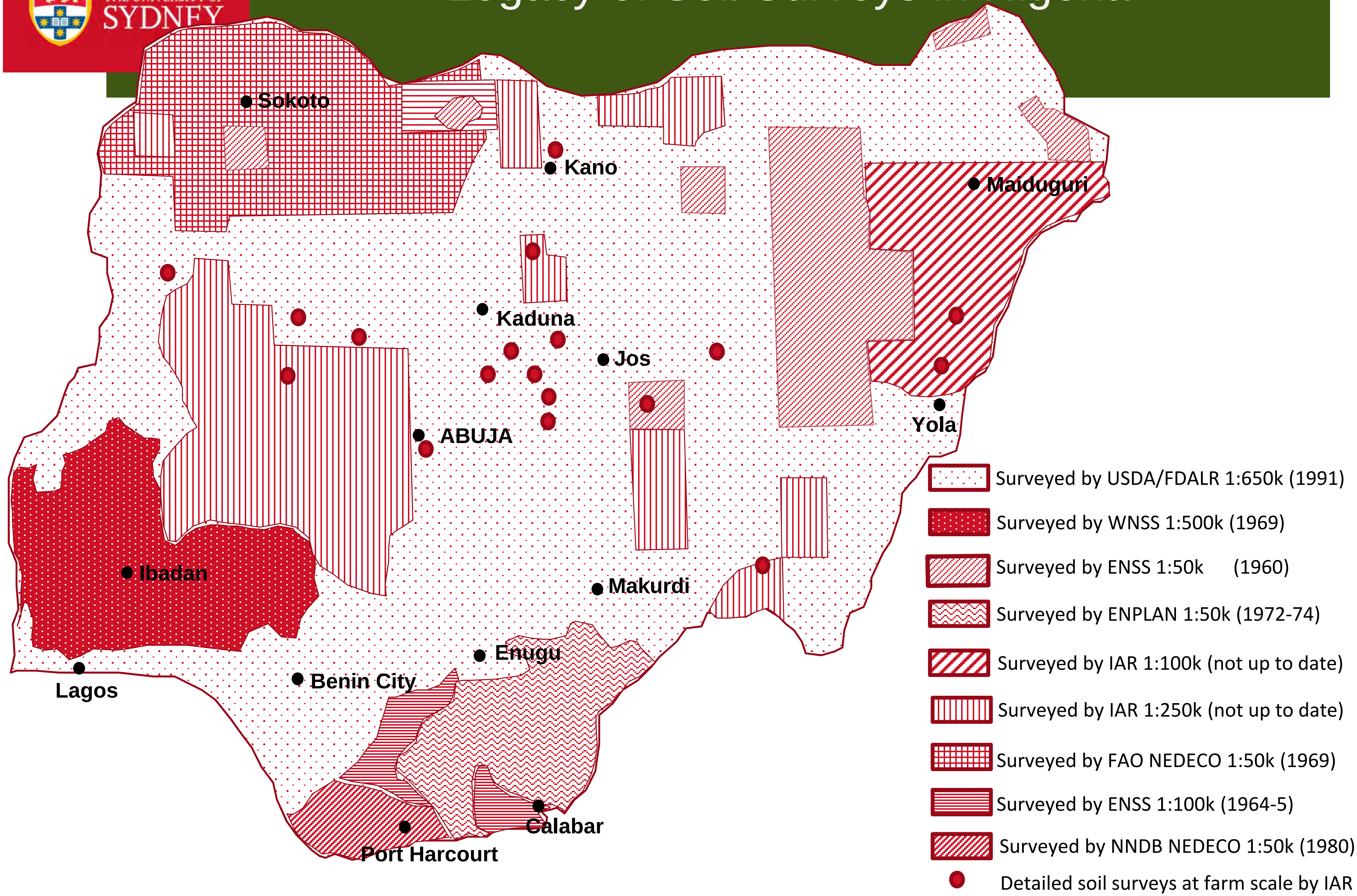
Soil Map of Nigeria by FDALR Published in 1991: Scale 1:650k, funded by USDA in the 1980s

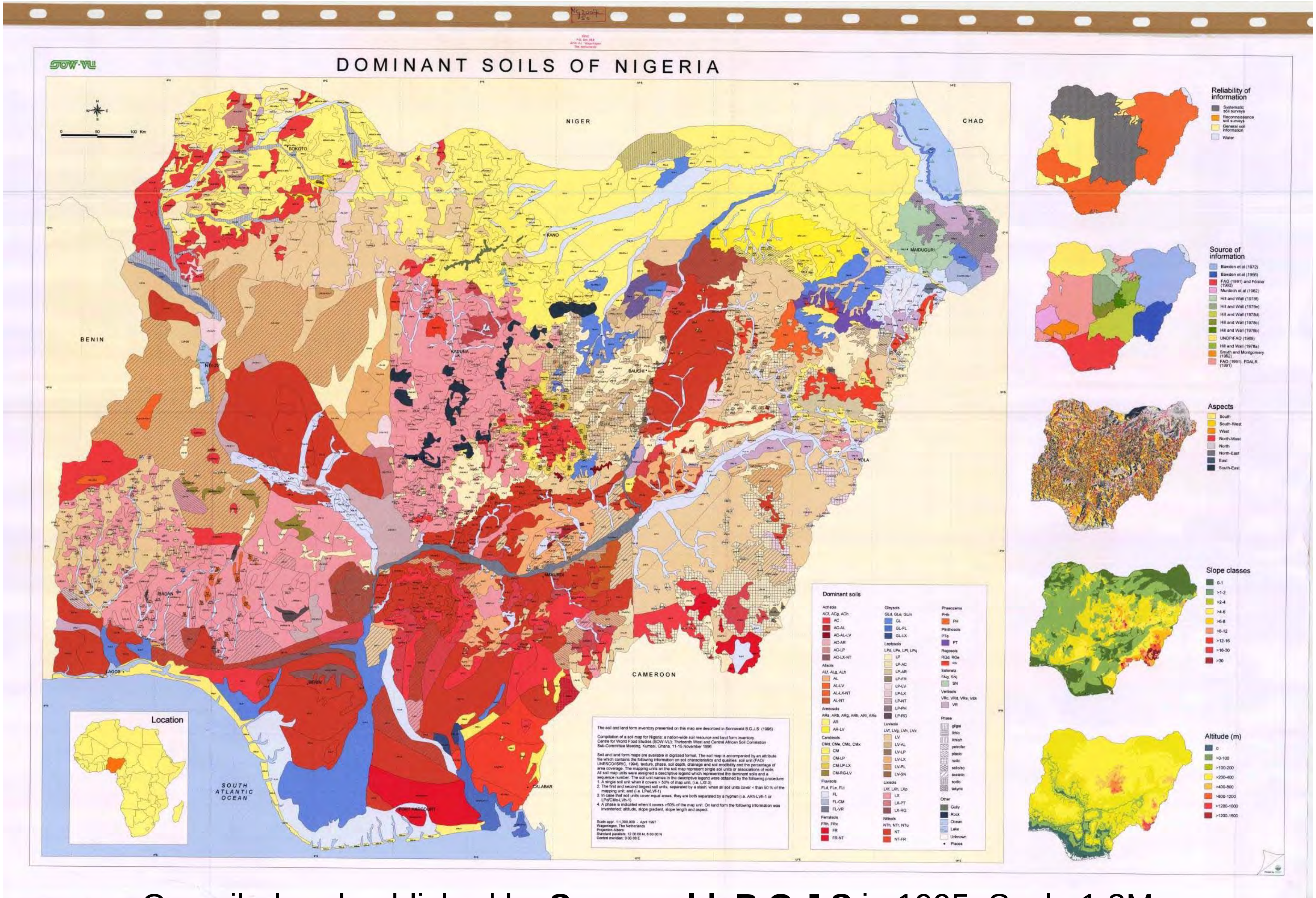
Legacy of Soil Surveys in Nigeria

Thus these soil surveys were produced by different institutions or organizations :

- Departments within a number of Federal Ministries- variably include Agriculture, Environment and Natural Resources- example are the FDALR and National Program for Food Security. both now within the Federal Ministry of Agriculture;
- Overseas Development Aid Organizations such as the British owned Land Resource Division of the Overseas Development Administration and USDA;
- Former Regional Government Ministries of Agriculture and affiliated Institutions
- River Basin Development Authorities of which there are currently 12;
- Government-funded Research Institutions within or outside Universities;
- Individuals within Faculties of Agricultures in various Universities and Colleges of Agriculture;
- Private sectors- large farm projects; reports indicate that only a limited number in this category have some form of soil profiles data

Legacy of Soil Surveys in Nigeria

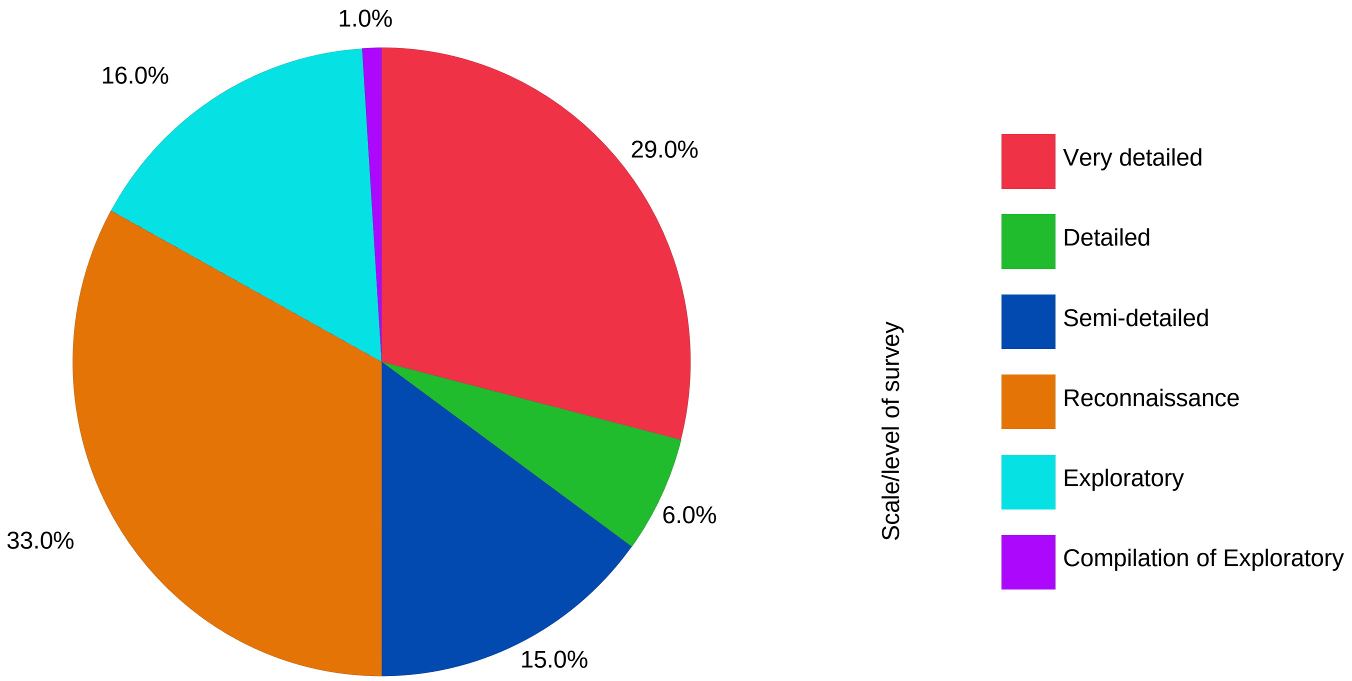




Compiled and published by **Sonneveld, B.G.J.S** in 1995: Scale 1:3M

Legacy of Soil Surveys in Nigeria

Proportion of soil surveys in Nigeria



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Digital Soil Mapping For Nigeria

Because of my expertise in DSM and my passion for *GolbalSoilMap.net* project to succeed in Nigeria, and in Africa in general:

- I convinced the University of Sydney to use my 6-month sabbatical at ISRIC- to initiate the first approximation of DSM for Nigeria as an exemplar for Africa;
  - Collaboration with African and ISRIC scientists

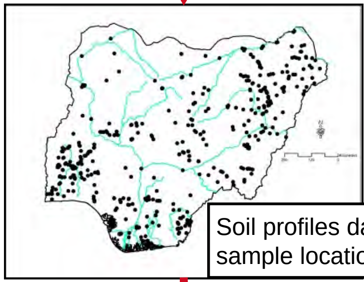
Digital Soil Mapping For Nigeria

DSM Steps for Nigeria (following Rossiter, 2008):

Data archeology- locating and cataloguing of soil legacy data

Data capture- scanning and digitisation of analogue soil legacy data

Data renewal- transformation of captured legacy data into usable digital database



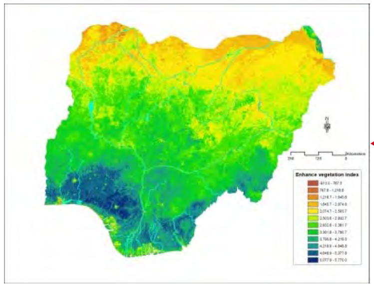
Soil profiles data at sample locations

Spline function- fit a spline function to each soil profile to estimate values at GSM standard depths

Acquisition and/or transformation of covariate data at fine (100m) grid

Use data mining tool (Cubist) to interpolate a soil property at each depth onto the fine grid

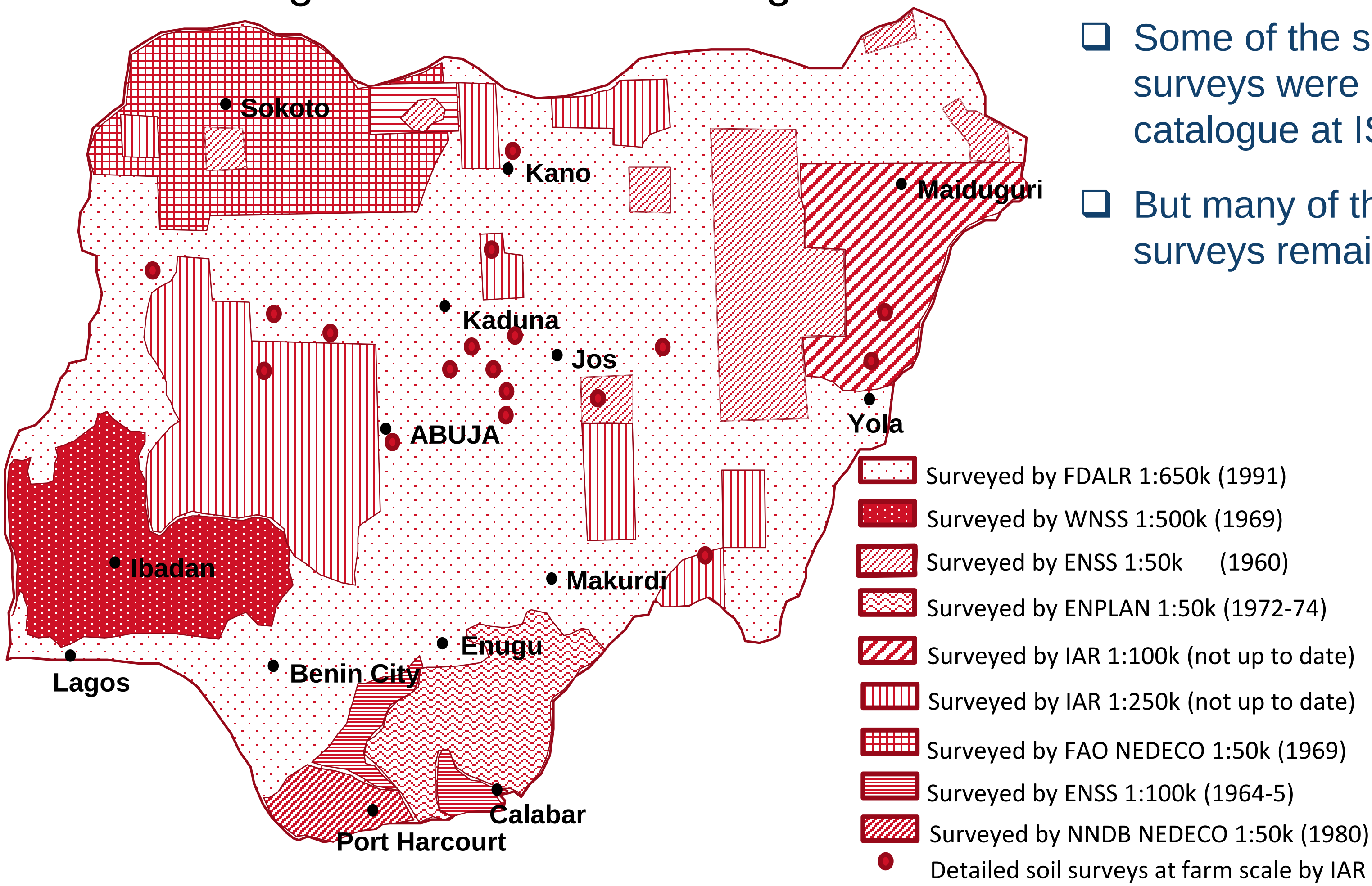
$$V_d = f(Q) + e$$



E.g., Digital map (100-m resolution) of a soil property at a given depth predicted from 572 locations and covariates

What were the challenges in legacy soil data renewal

Finding and locating the sources of legacy data is most challenging in the process leading to data renewal in Nigeria



- Some of the small scale surveys were already catalogue at ISRIC
- But many of the detailed surveys remain to be captured

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Challenges in legacy soil data renewal

› Ann then the renewal (digitisation & transformation) of analogue soil data in reports, maps and profile observations, is challenging depending on whether it is based on:

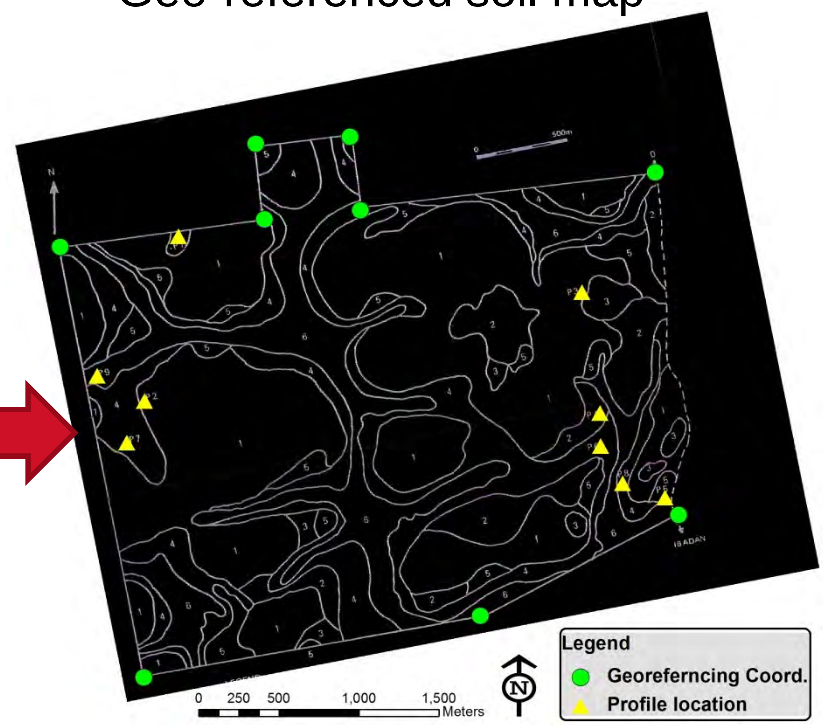
- Analogue-to-digital transformation of georeferenced analogues with known projections and datums
- Analogue-to-digital transformation of georeferenced analogues with unknown projections and datums
- Analogue-to-digital transformation of un-referenced analogue scaled (sampling) maps with profile locations and accompanied by reports
- Analogue-to-digital legacy transformation of analogues with descriptive profile locations and reports

Challenges in legacy soil data renewal

An example of analogue-to-digital transformation of un-referenced analogue scaled map

Scanned soil map

Geo-referenced soil map



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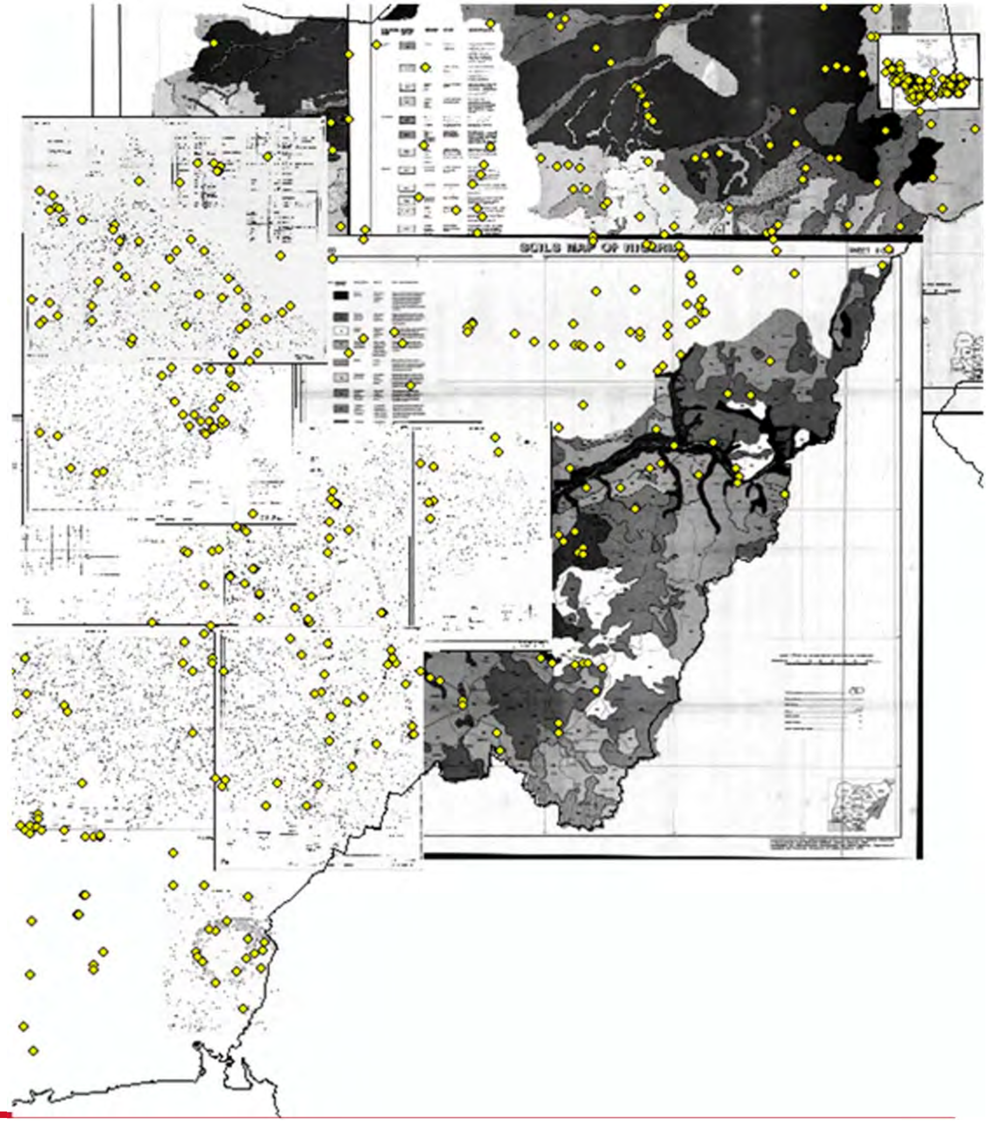
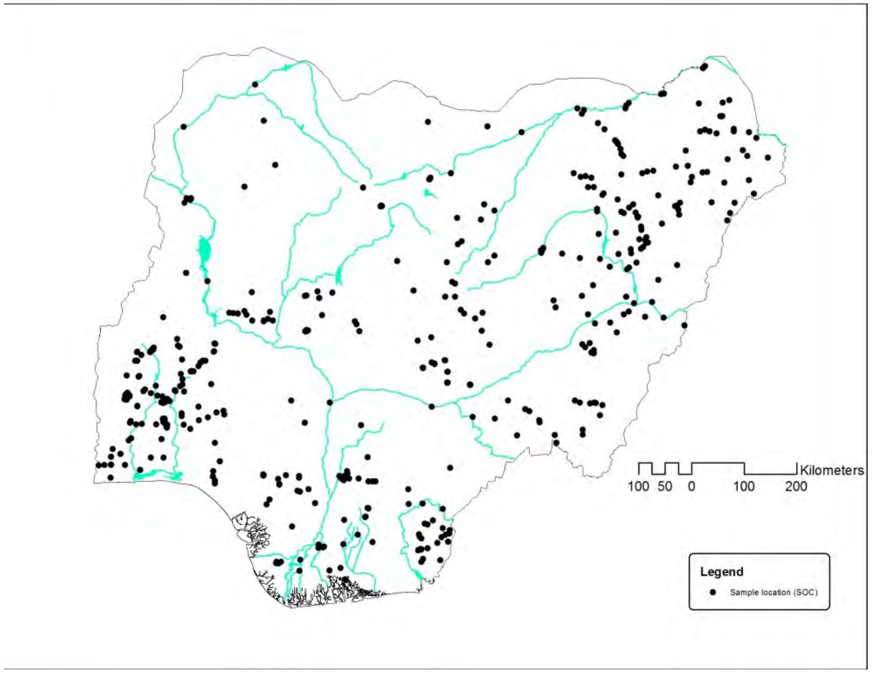
Challenges in legacy soil data renewal

Locations of profiles in northeastern Nigeria by the combined use of Google Earth and mapping units and representative profiles as auxiliary information.



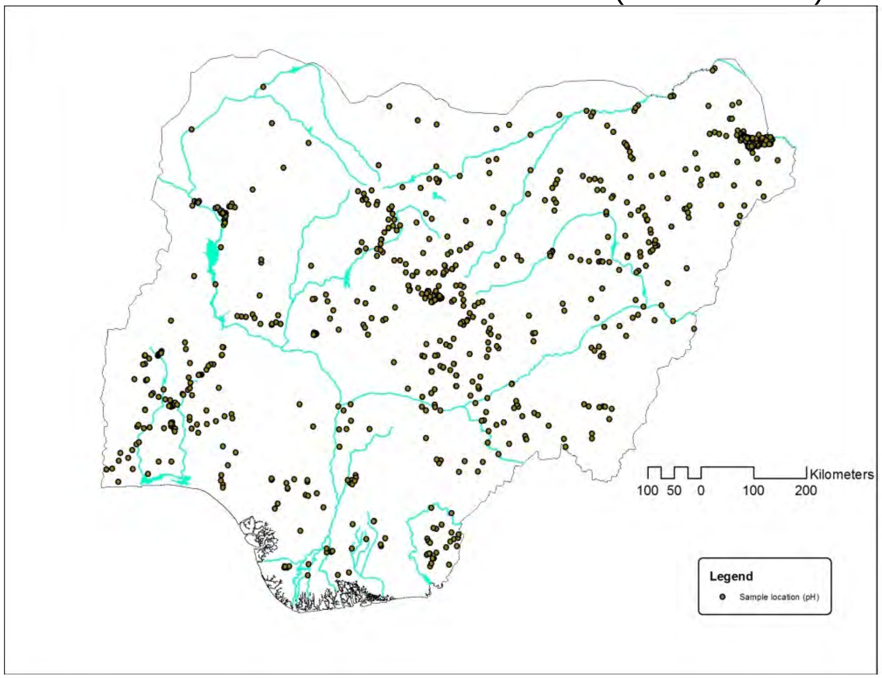
Some outcomes

Sample locations- soil organic carbon



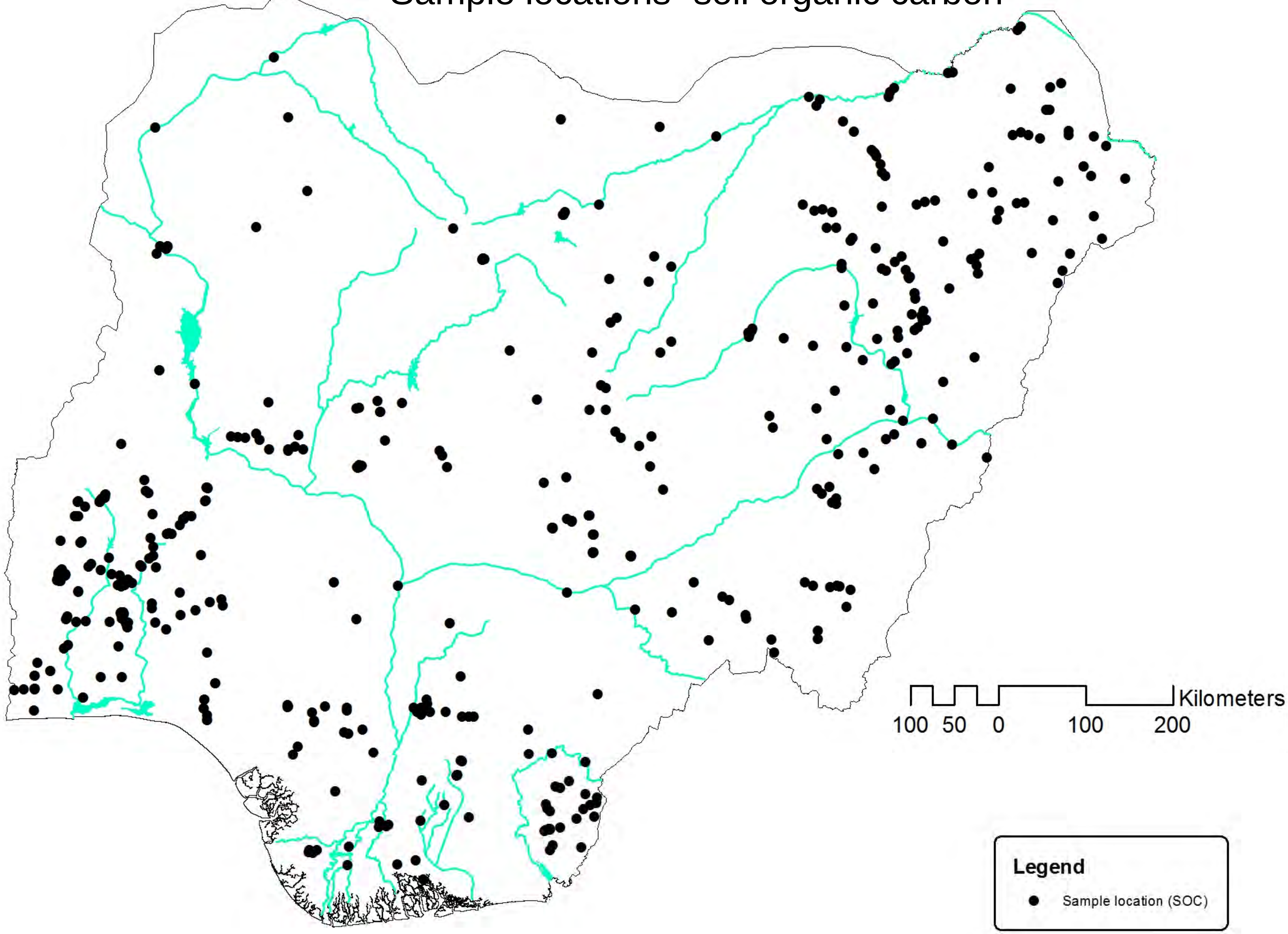
615 profile locations with at least SOC data at 3 or more horizons

Sample locations- soil pH$_{(1:5\ \text{soil-water})}$

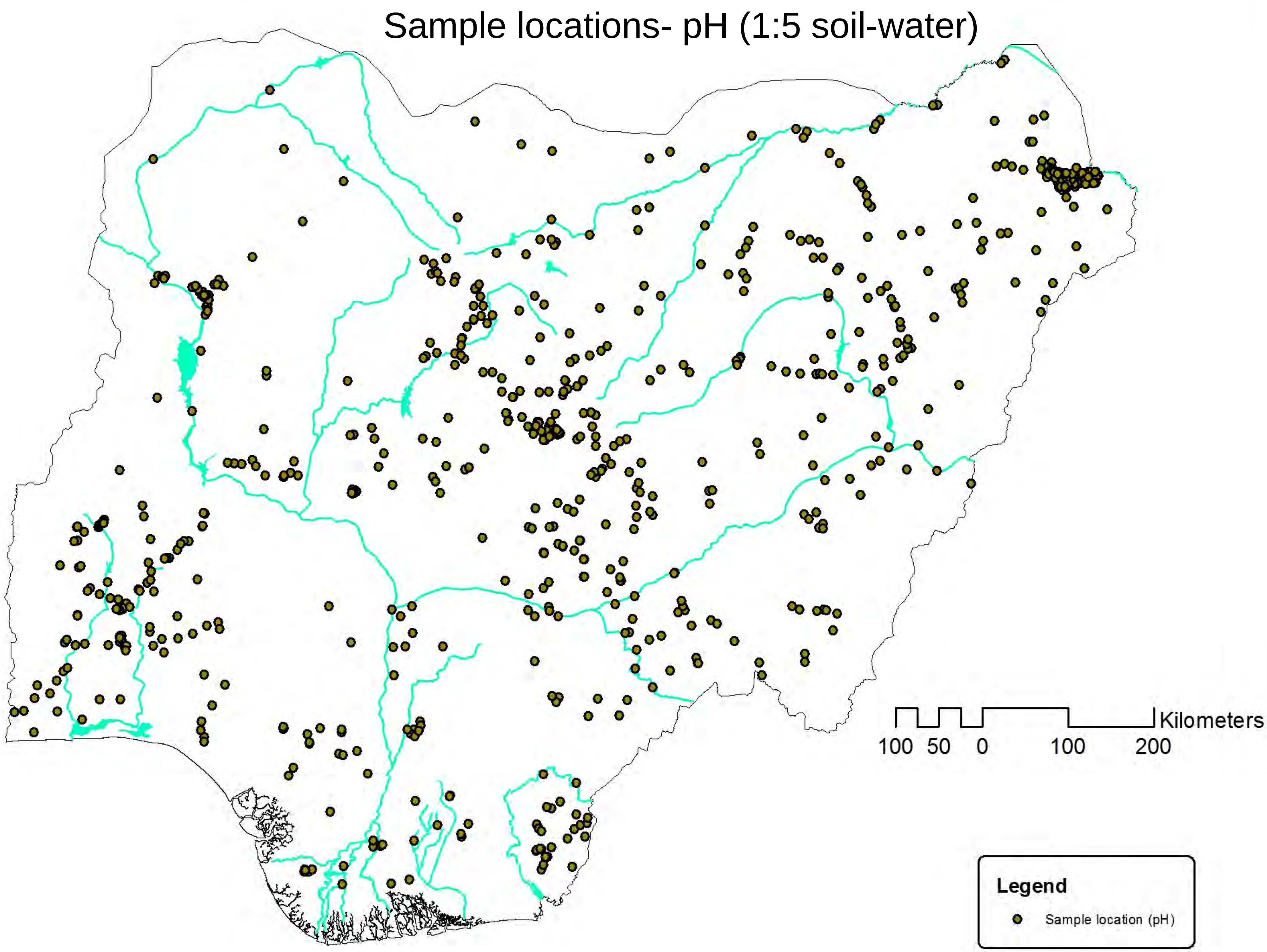


880 profile locations with at least soil pH data at 3 or more horizons

Sample locations- soil organic carbon



$N = 615$


Sample locations- pH (1:5 soil-water)
Kilometers
100 50 0 100 200
Legend
Sample location (pH)

N = 878

Fitting of Spline Funtions to the Legacy Profile Data

Data archeology- locating and cataloguing of soil legacy data

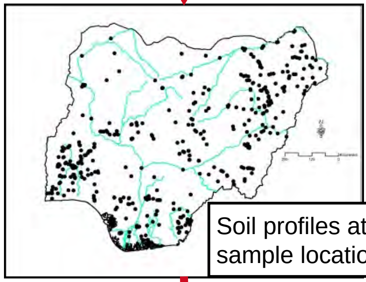
Data capture- scanning and digitisation of analogue soil legacy data

Data renewal- transformation of captured legacy data into usable digital database

Acquisition and/or transformation of covariate data at fine (100m) grid

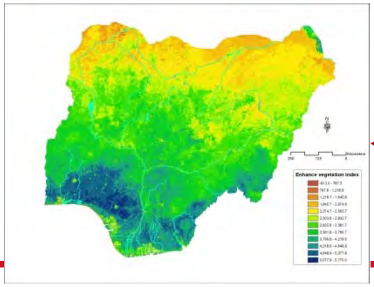
Use data mining tool (Cubist) to interpolate a soil property at each depth onto the fine grid

$$V_d = f(Q) + e$$



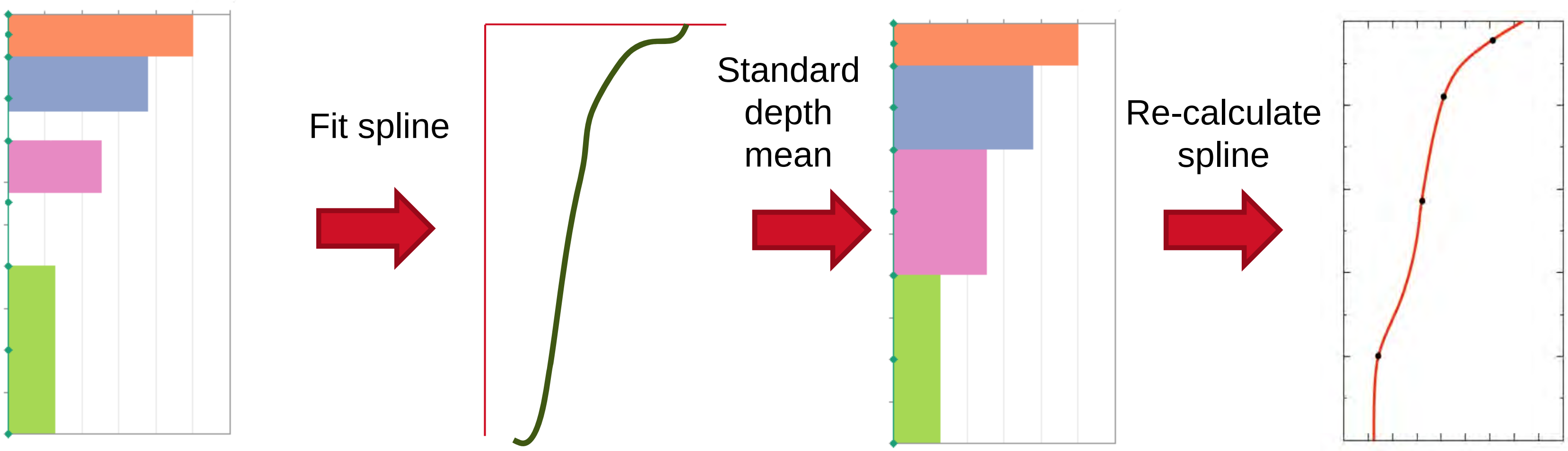
Soil profiles at sample locations

Spline function- fit a spline function to each soil profile to estimate values at GSM standard depths



E.g., Digital map (100-m resolution) of a soil property at a given depth predicted from 572 locations and covariates

Steps for fitting spline functions and estimating values at GSM standard depths

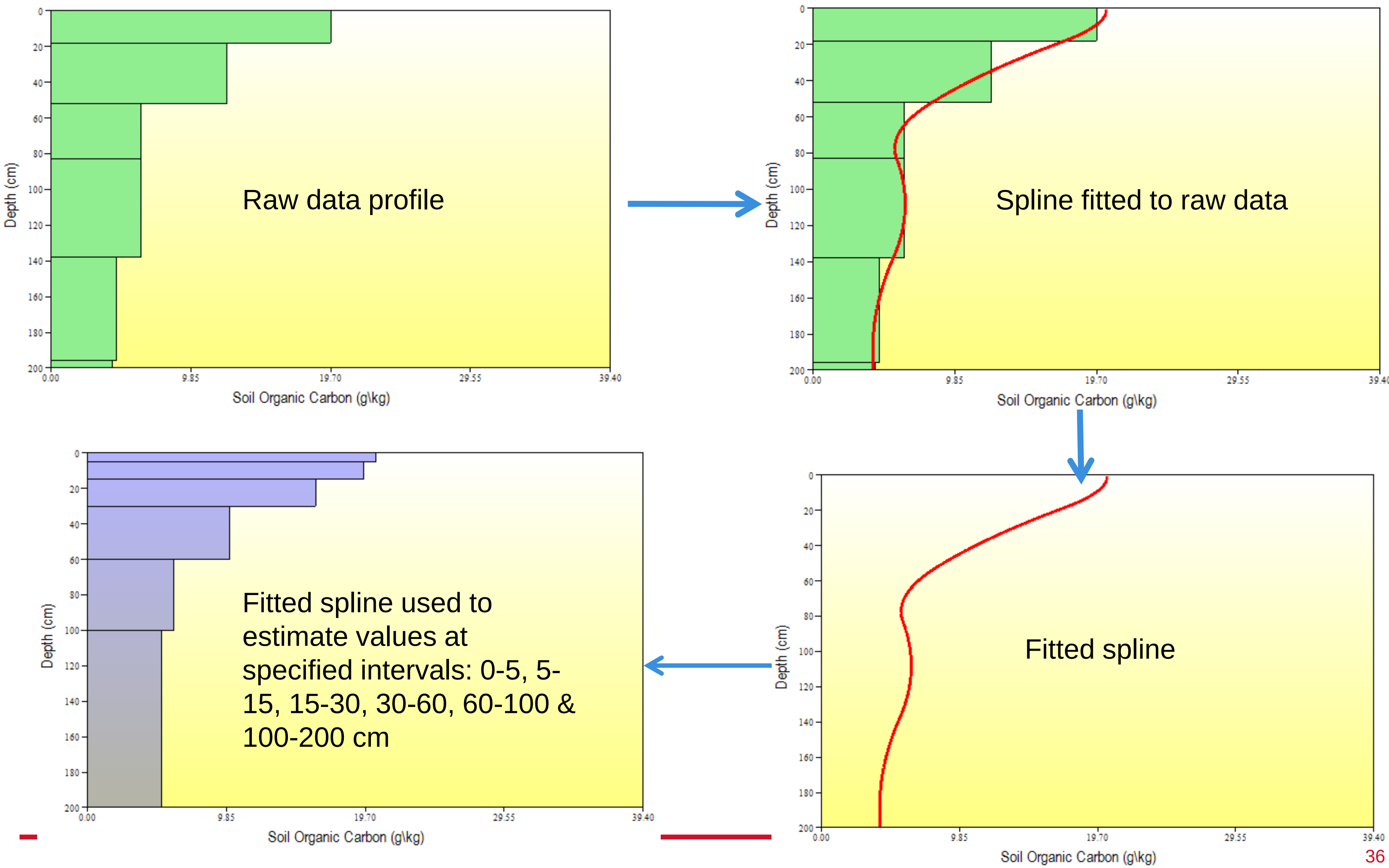


Real soil profile data
-variable intervals
-missing data

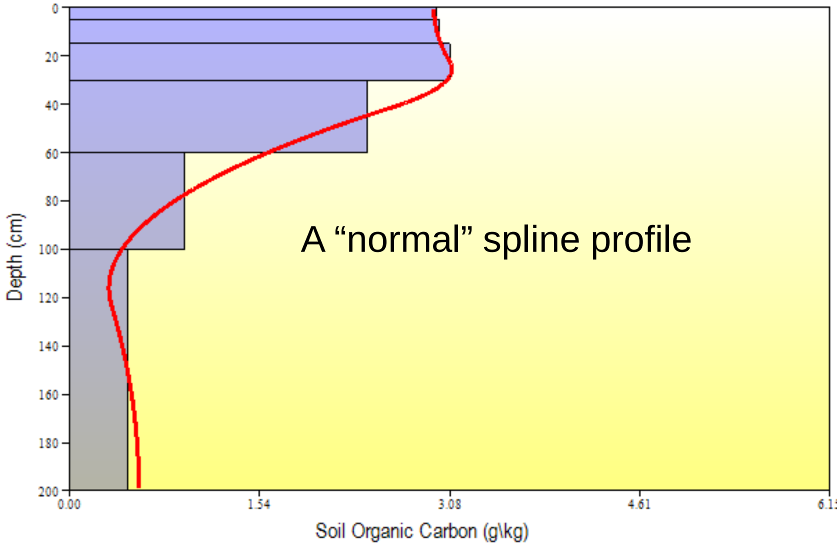
GlobalSoilMap
standard depths

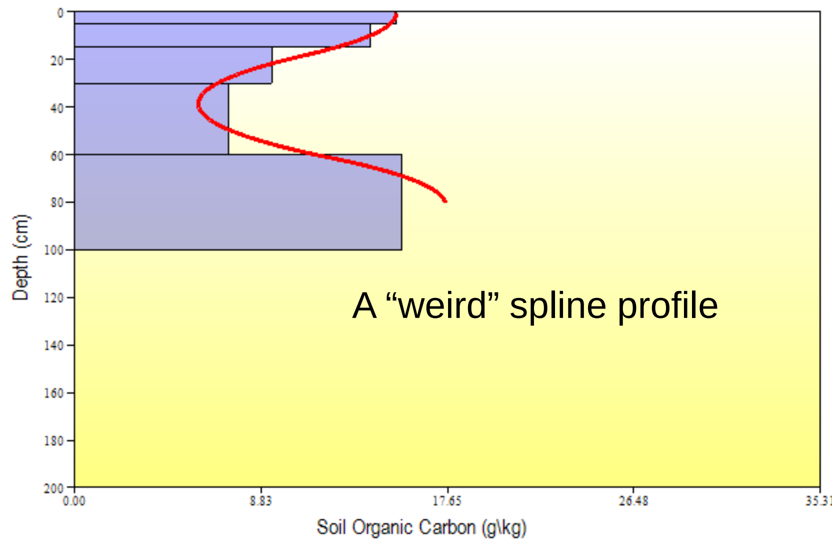
Depth spline
function

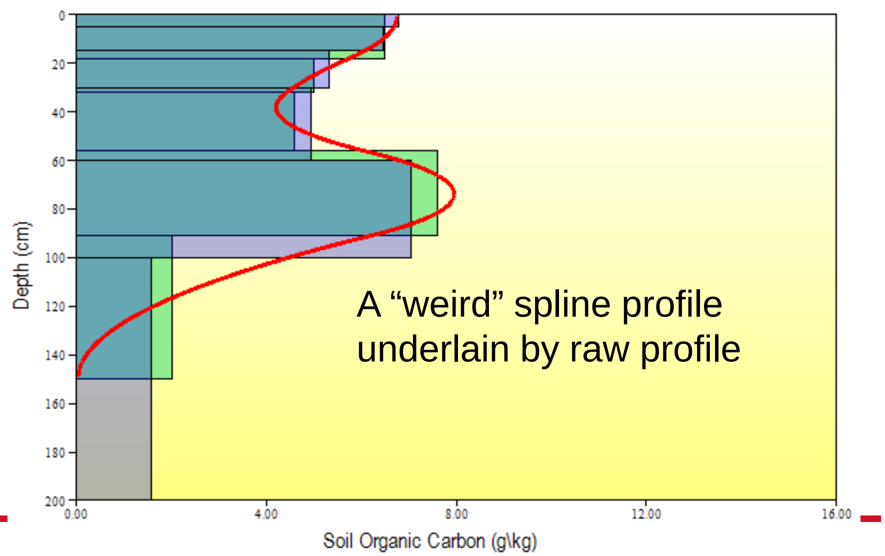
Fitting of spline functions and estimating values at GSM standard depths- examples

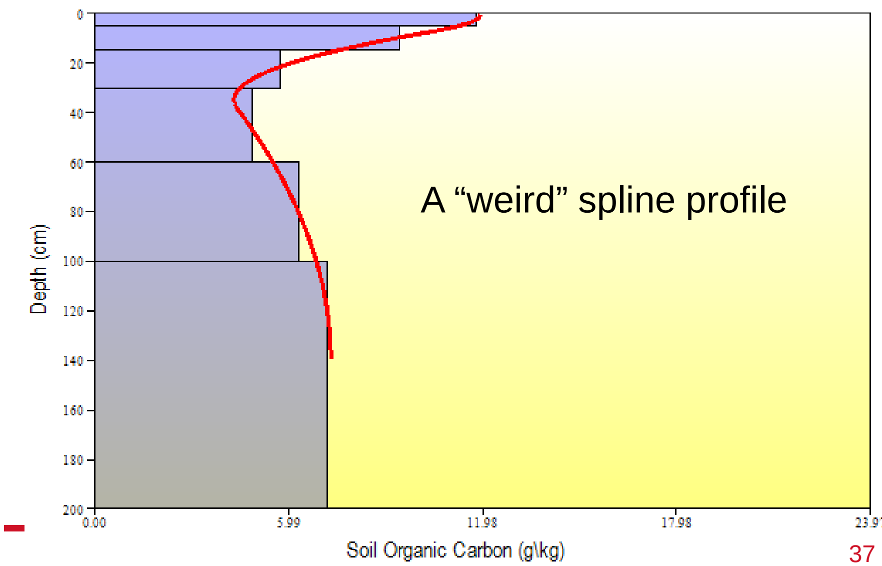


Selected fitted splines to SOC profiles

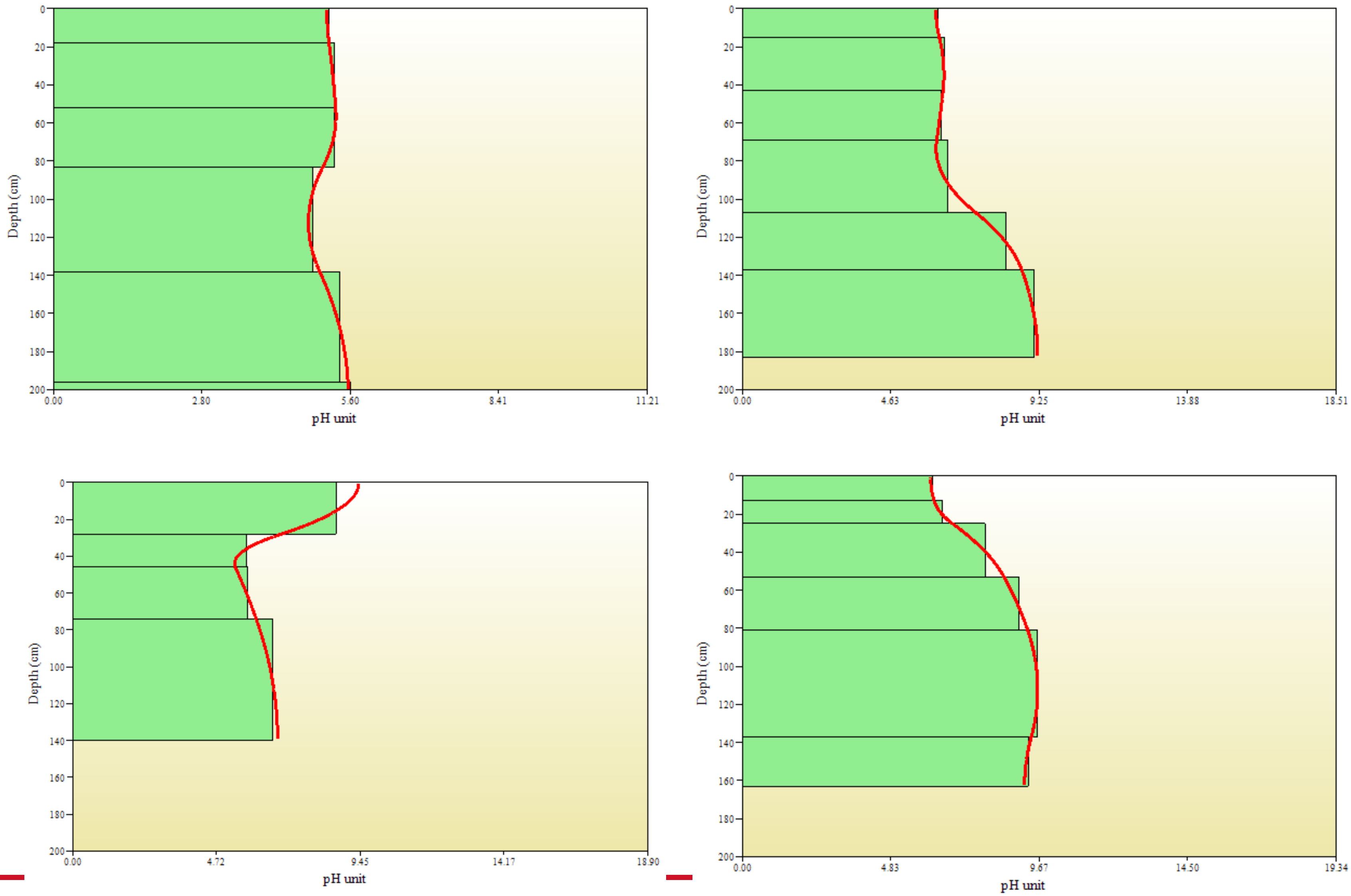


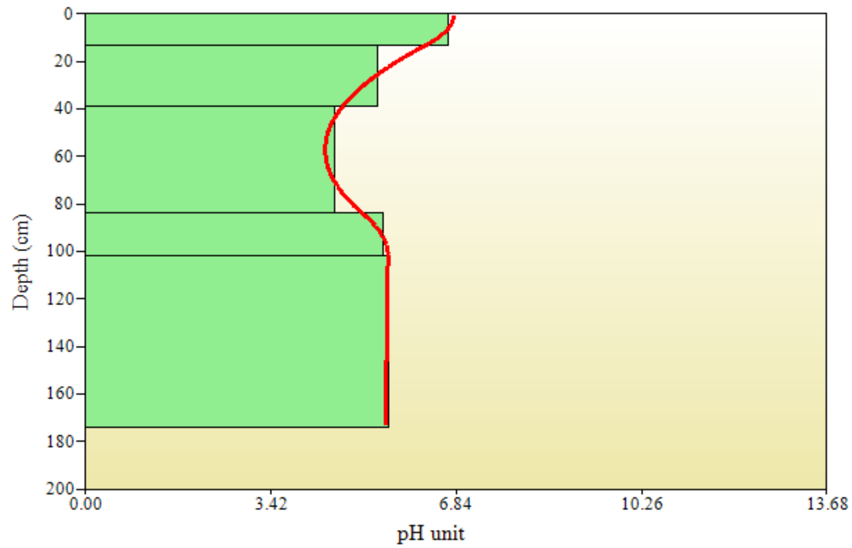


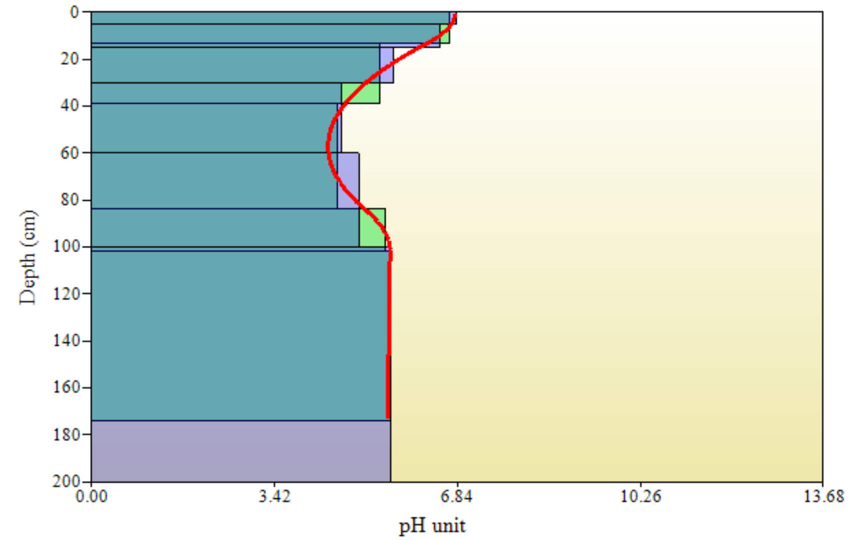




Selected fitted splines to pH profiles




Depth (cm)
0
20
40
60
80
100
120
140
160
180
200
0.00
3.42
6.84
10.26
13.68
pH unit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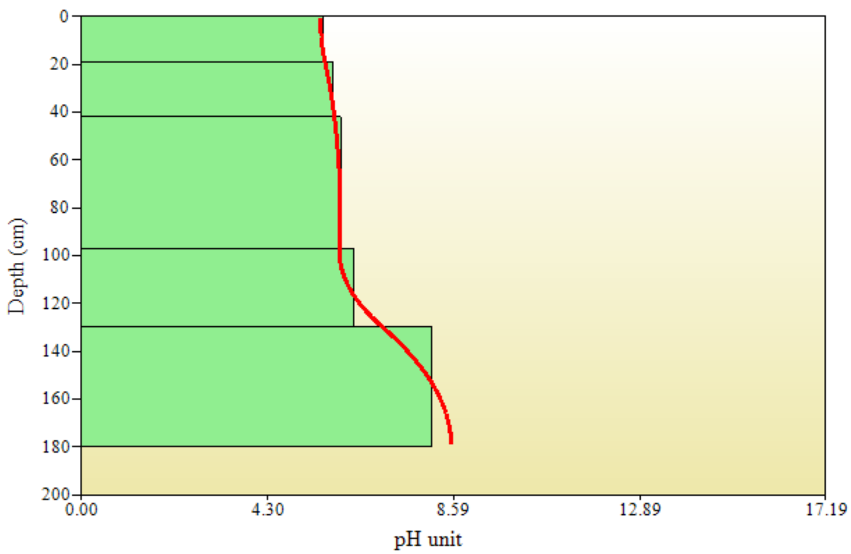
Depth (cm)
0
20
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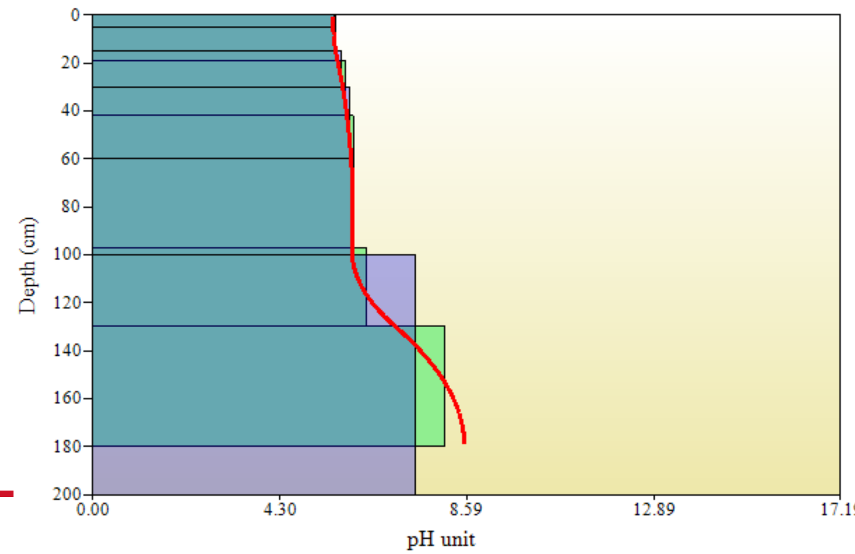
80
100
120
140
160
180
200
0.00
4.30
8.59
12.89
17.19
pH unit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0
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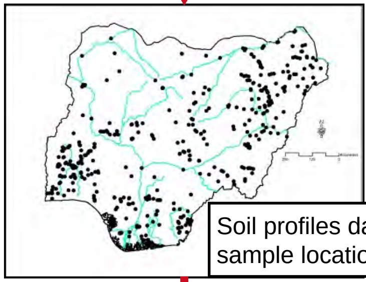
pH unit

Why Do We Need the Covariates

Data archeology- locating and cataloguing of soil legacy data

Data capture- scanning and digitisation of analogue soil legacy data

Data renewal- transformation of captured legacy data into usable digital database



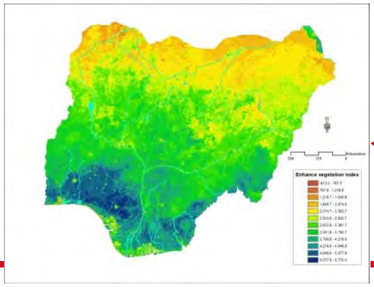
Soil profiles data at sample locations

Spline function- fit a spline function to each soil profile to estimate values at GSM standard depths

Acquisition and/or transformation of covariate data at fine (100m) grid

Use data mining tool (Cubist) to interpolate a soil property at each depth onto the fine grid

$$V_d = f(Q) + e$$



E.g., Digital map (100-m resolution) of a soil property at a given depth predicted from 572 locations and covariates

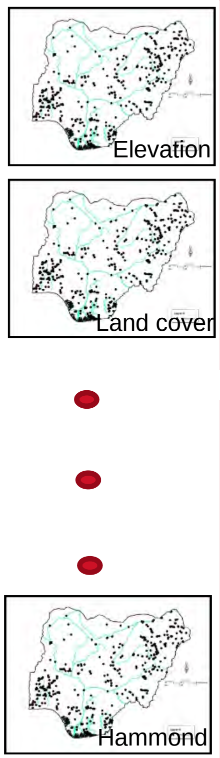
40

Why do we Need the Covariates

A: Use data at sample locations to generate a model relationship between a soil attribute and covariates

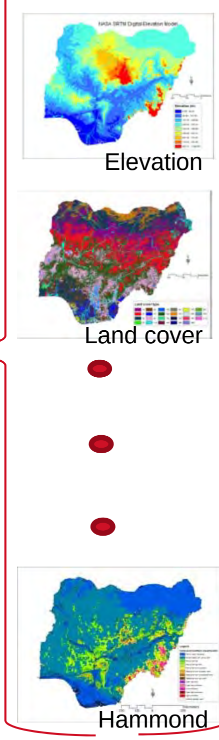
B: Use the model to populate the soil property from the covariate raster data at 100-m resolution

$V_d = f$

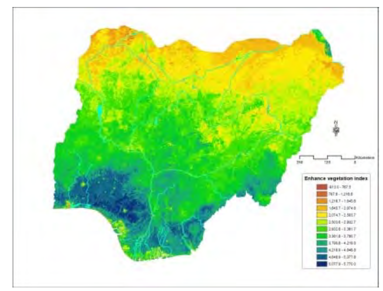


$+ e$

f

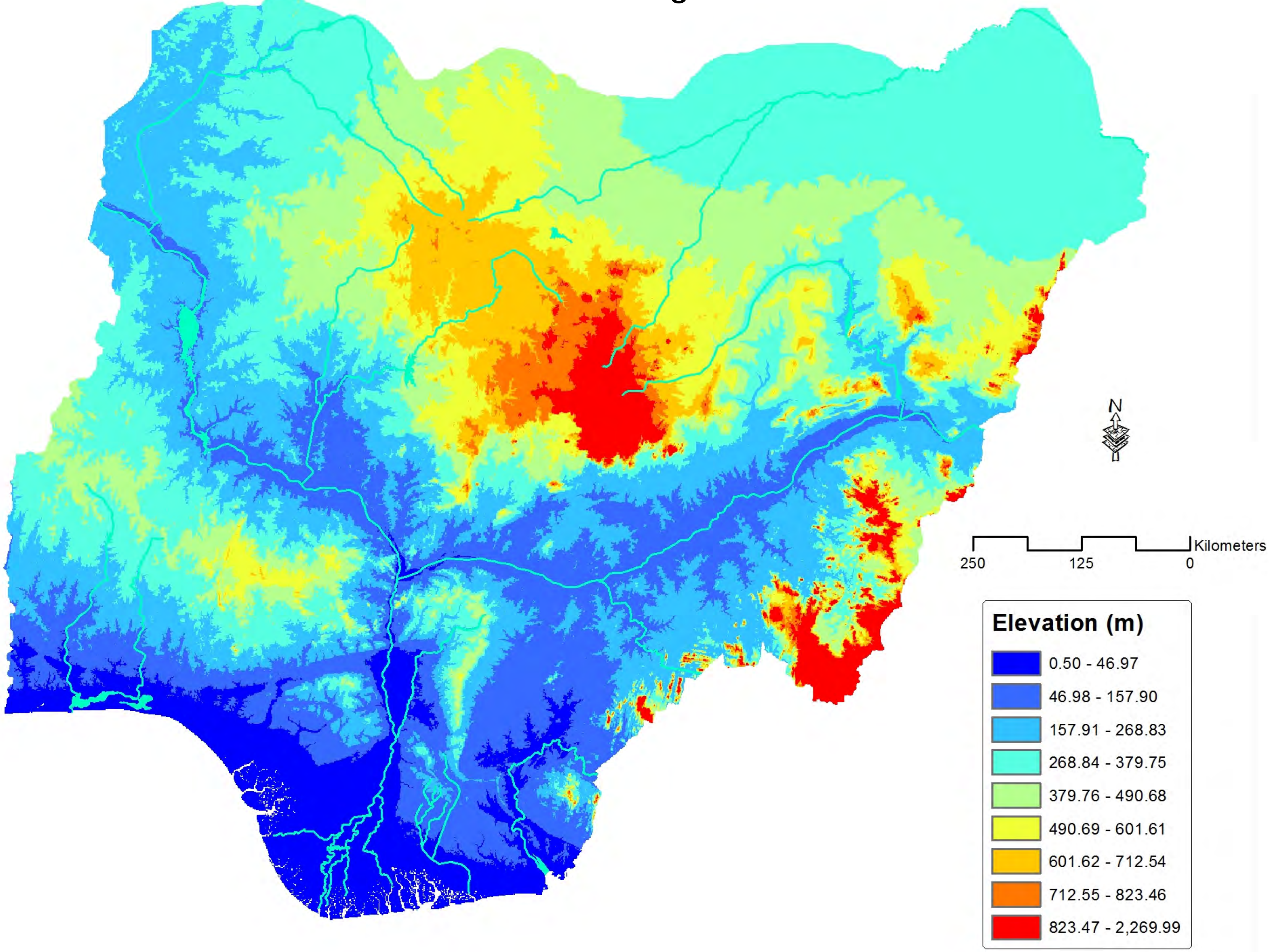


$=$

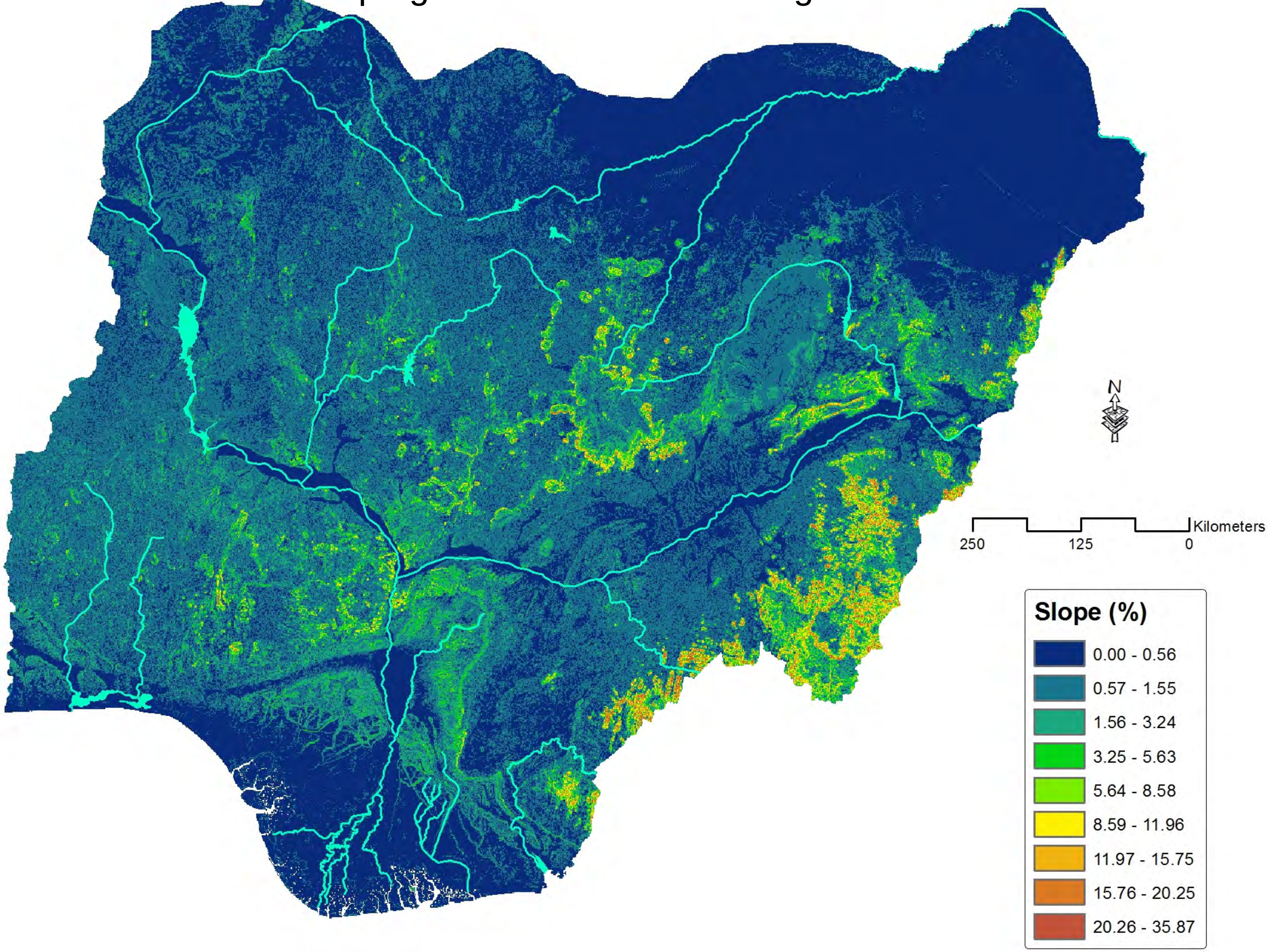


E.g., Digital map of 0-5 cm depth soil pH at 100-m resolution

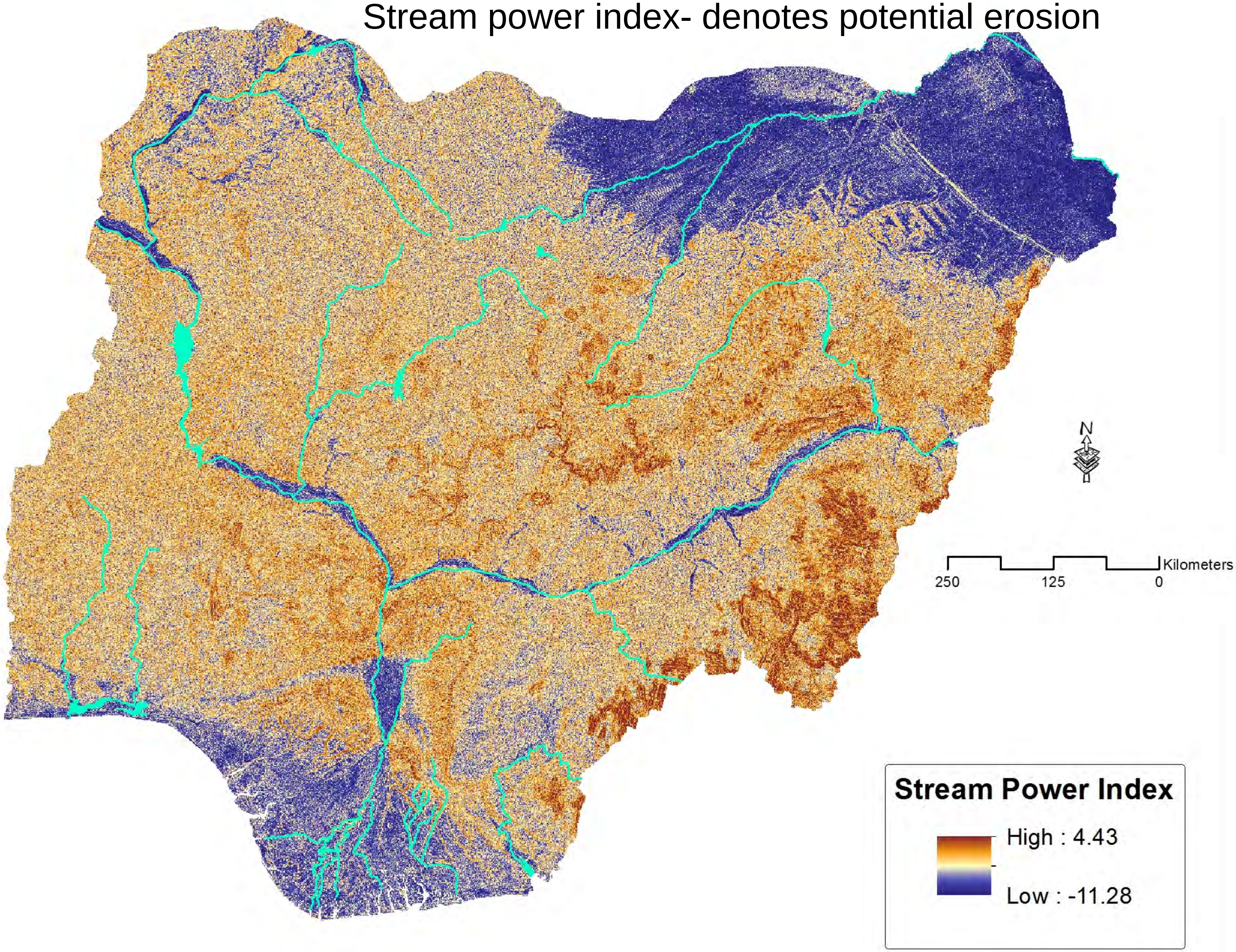
NASA SRTM 100-m resolution Digital Elevation Model



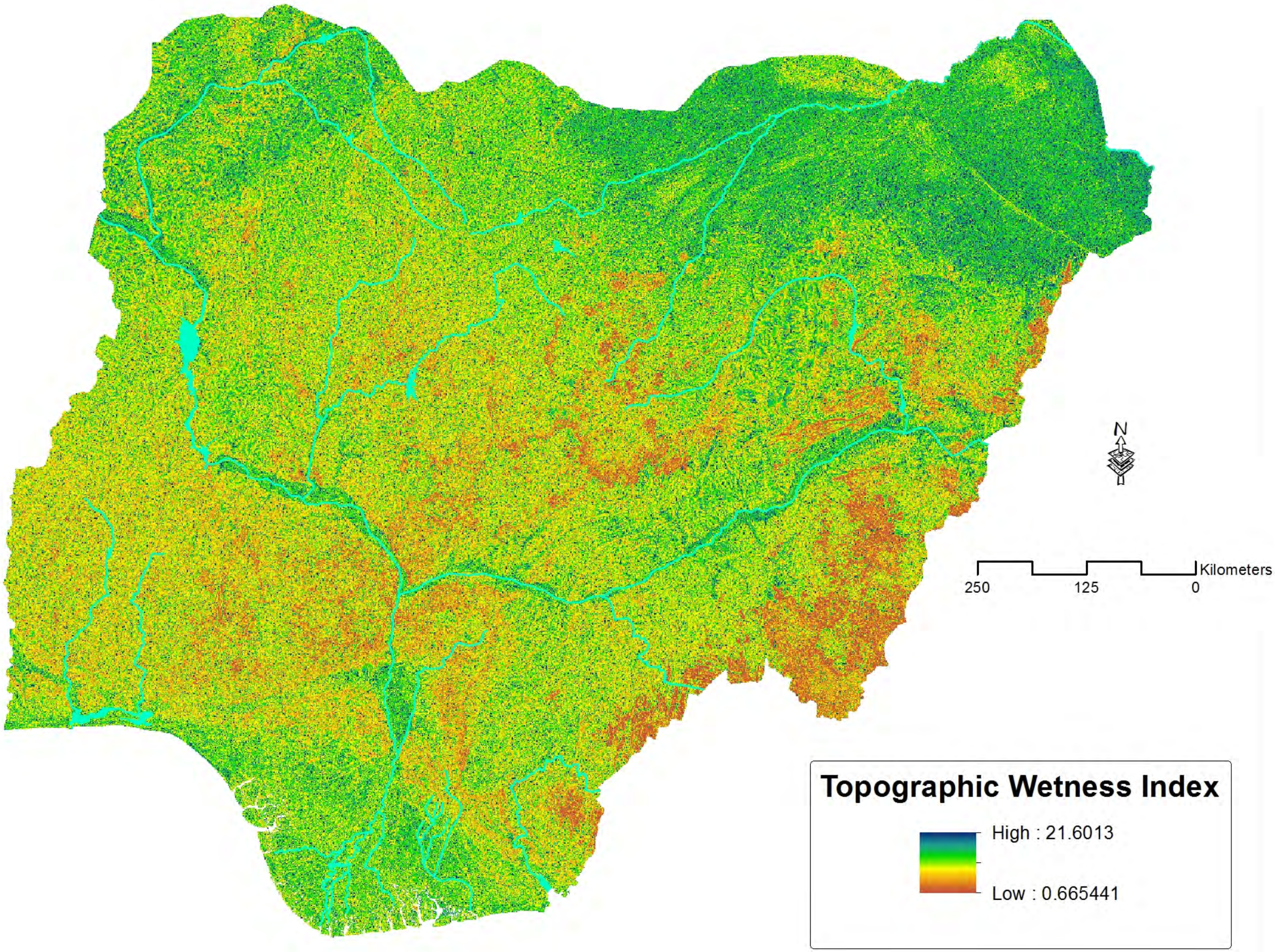
Slope gradient derived from digital elevation model

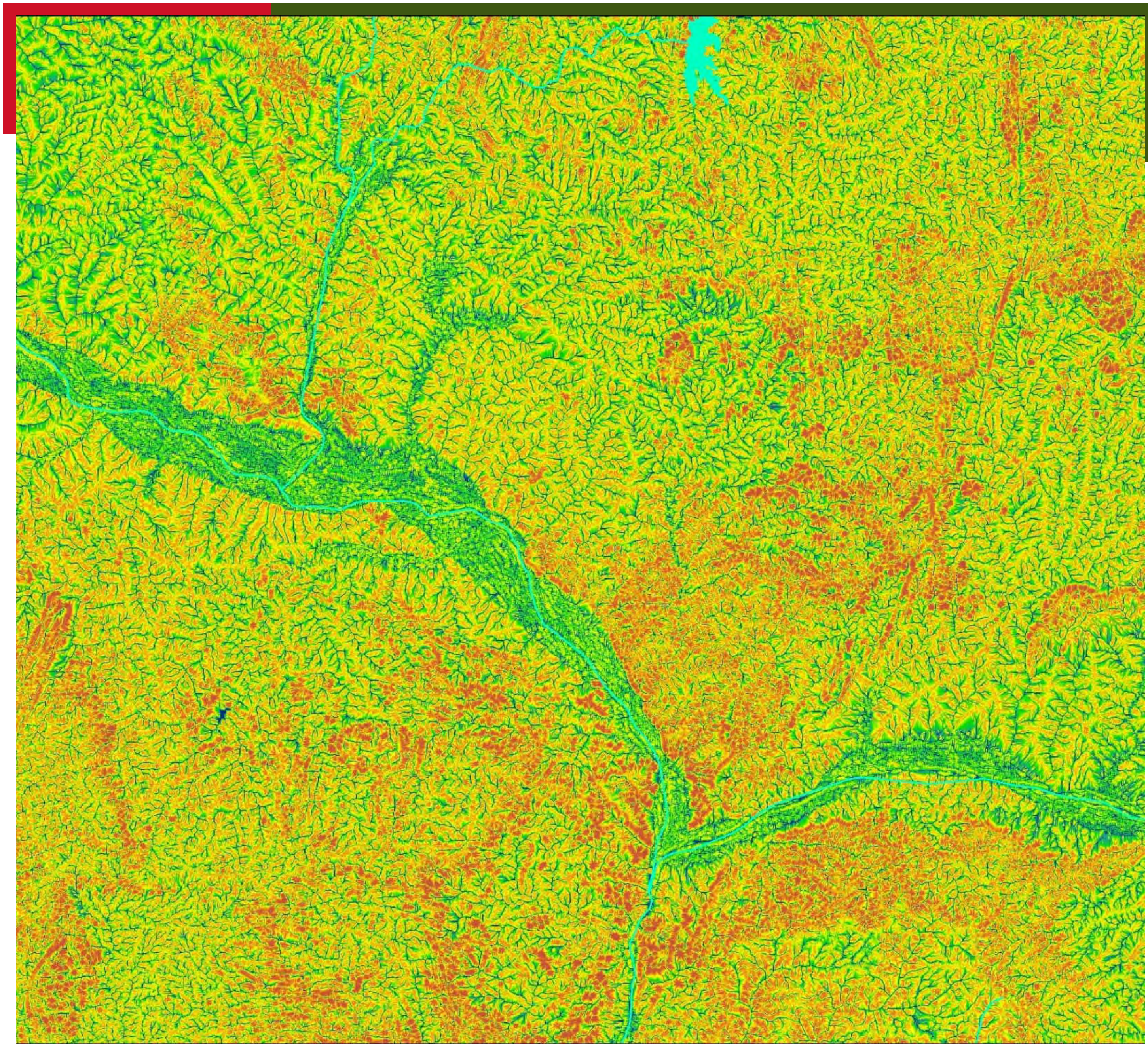


Stream power index- denotes potential erosion

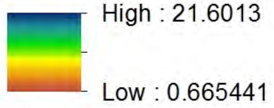


Topographic wetness index- denotes potential water accumulation

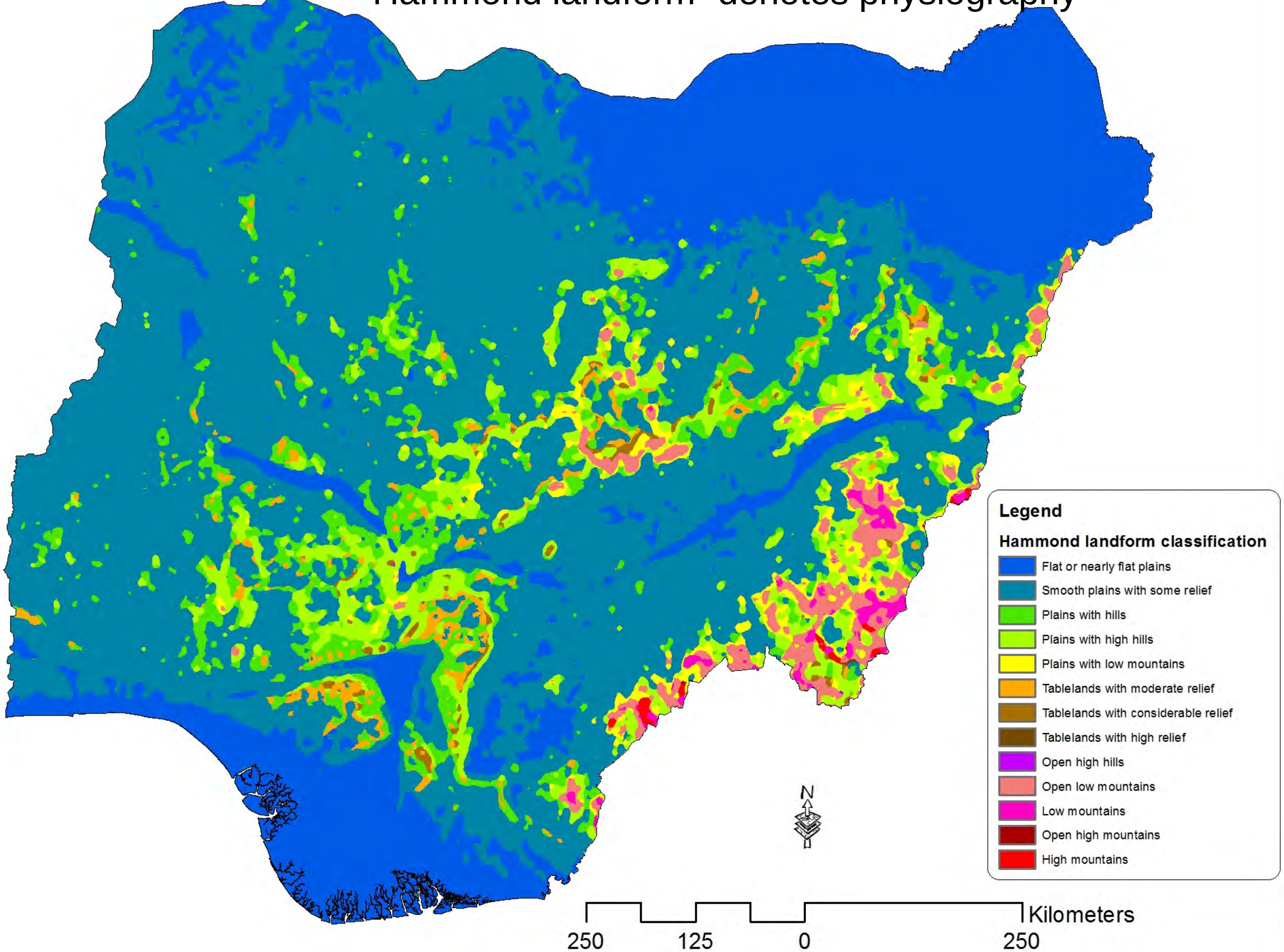




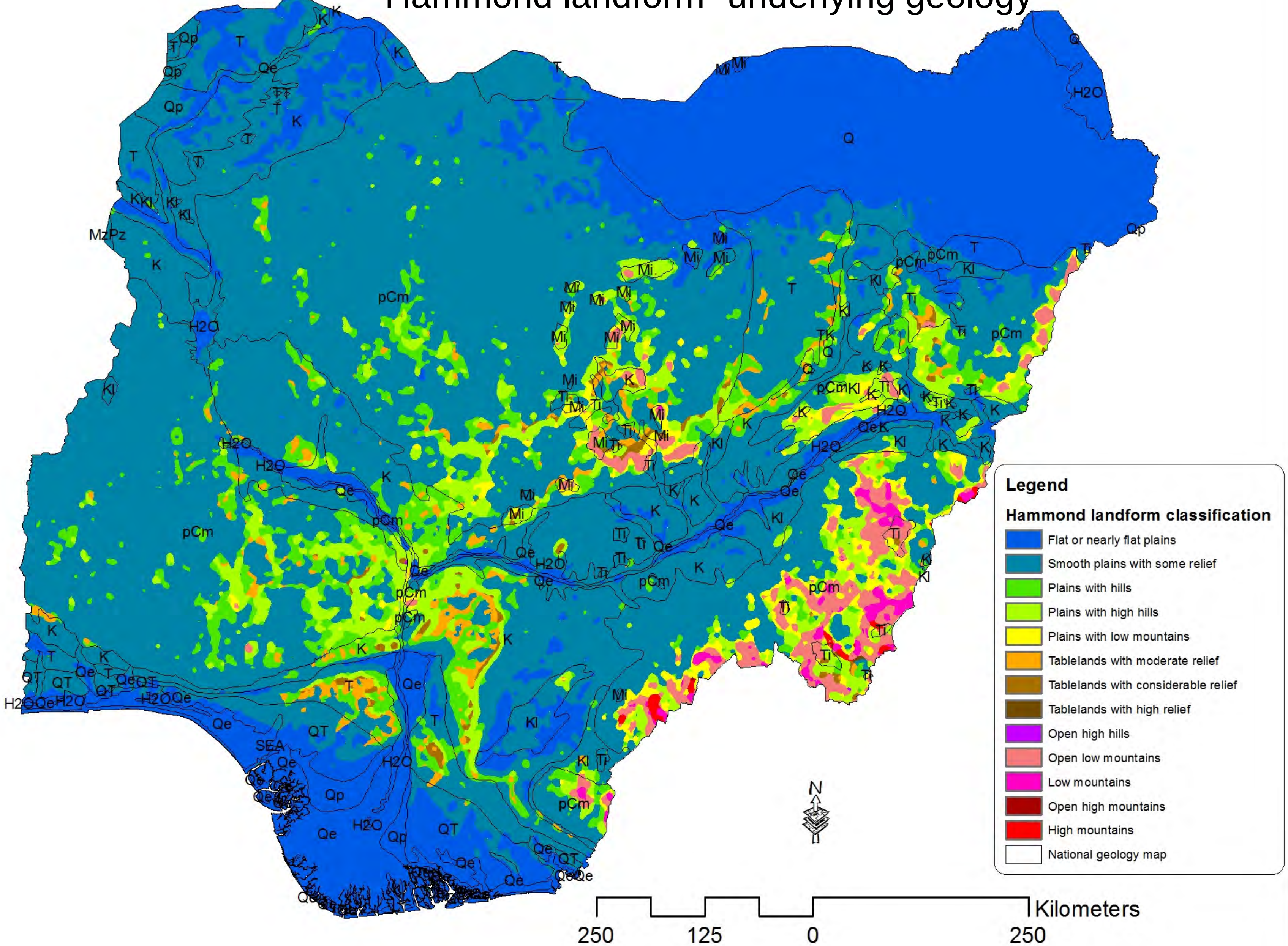
Zoomed TWI



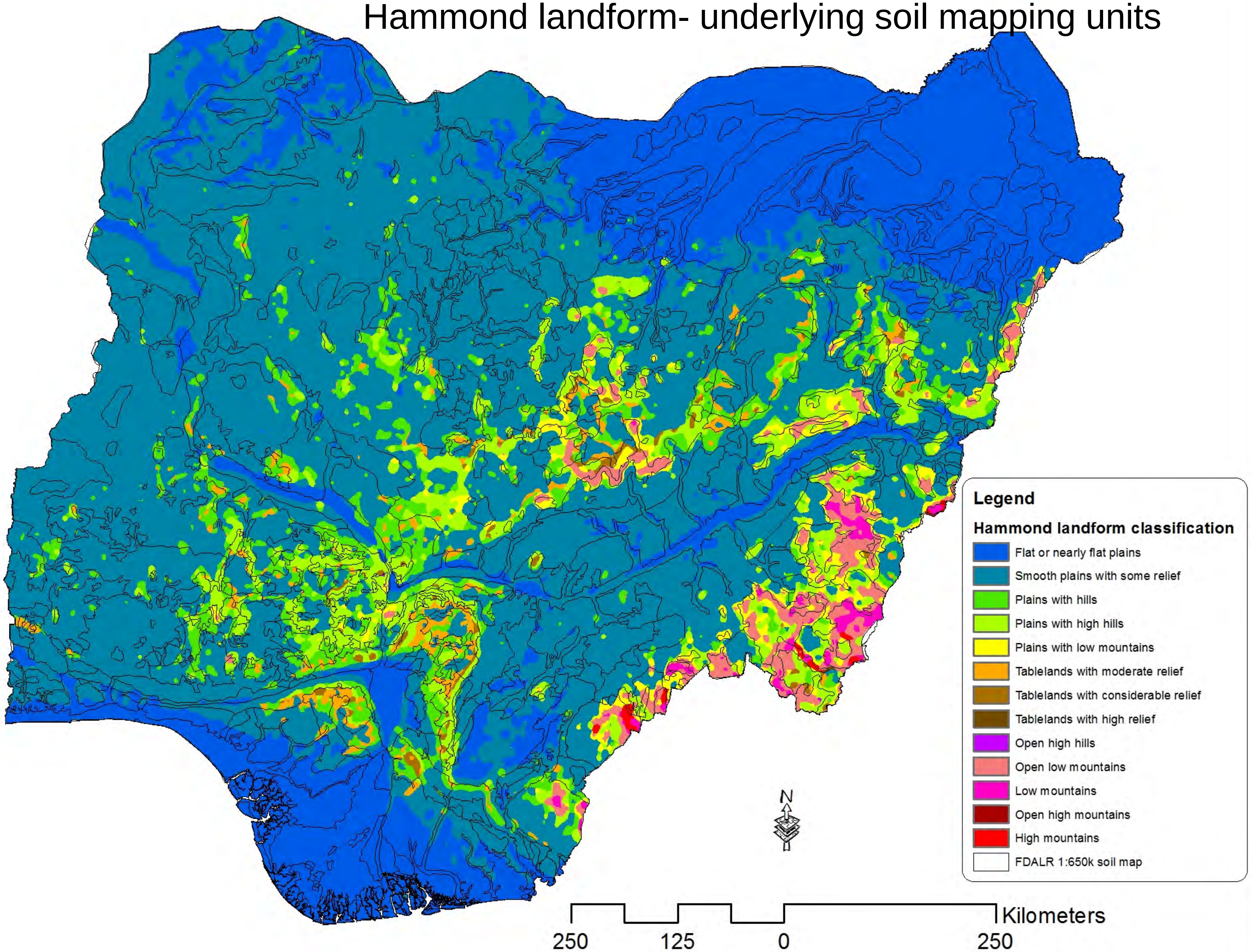
Hammond landform- denotes physiography



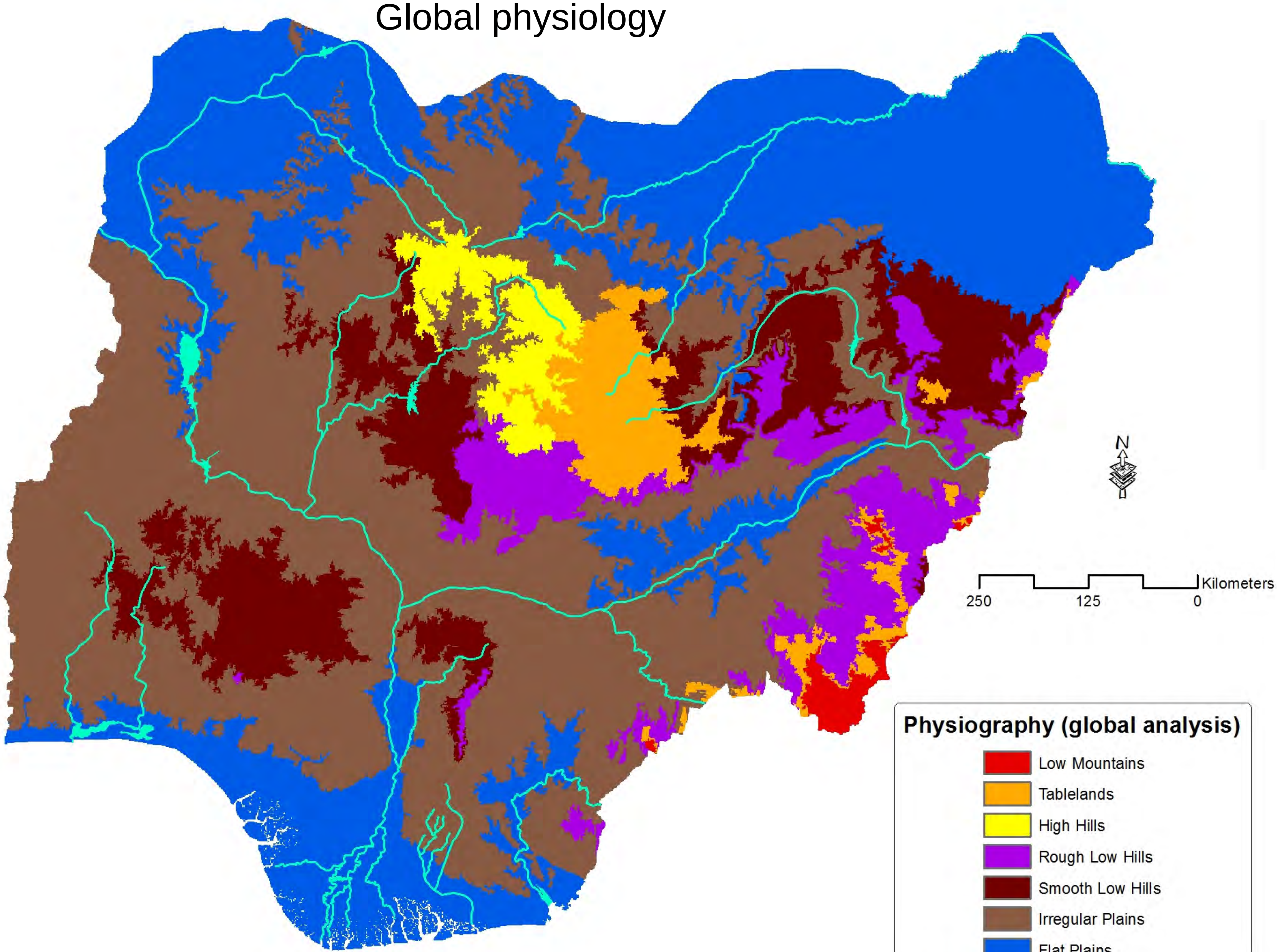
Hammond landform- underlying geology



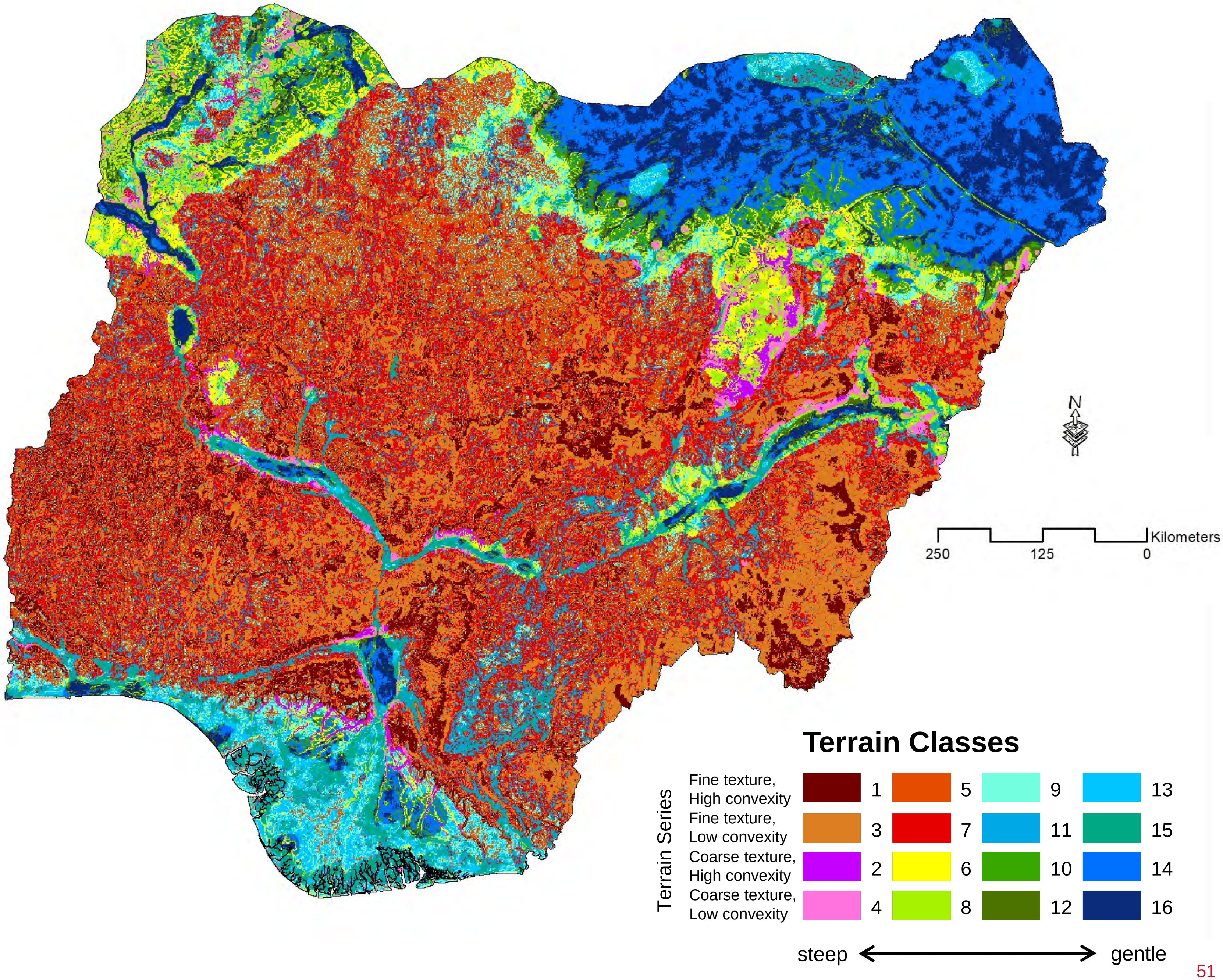
Hammond landform- underlying soil mapping units



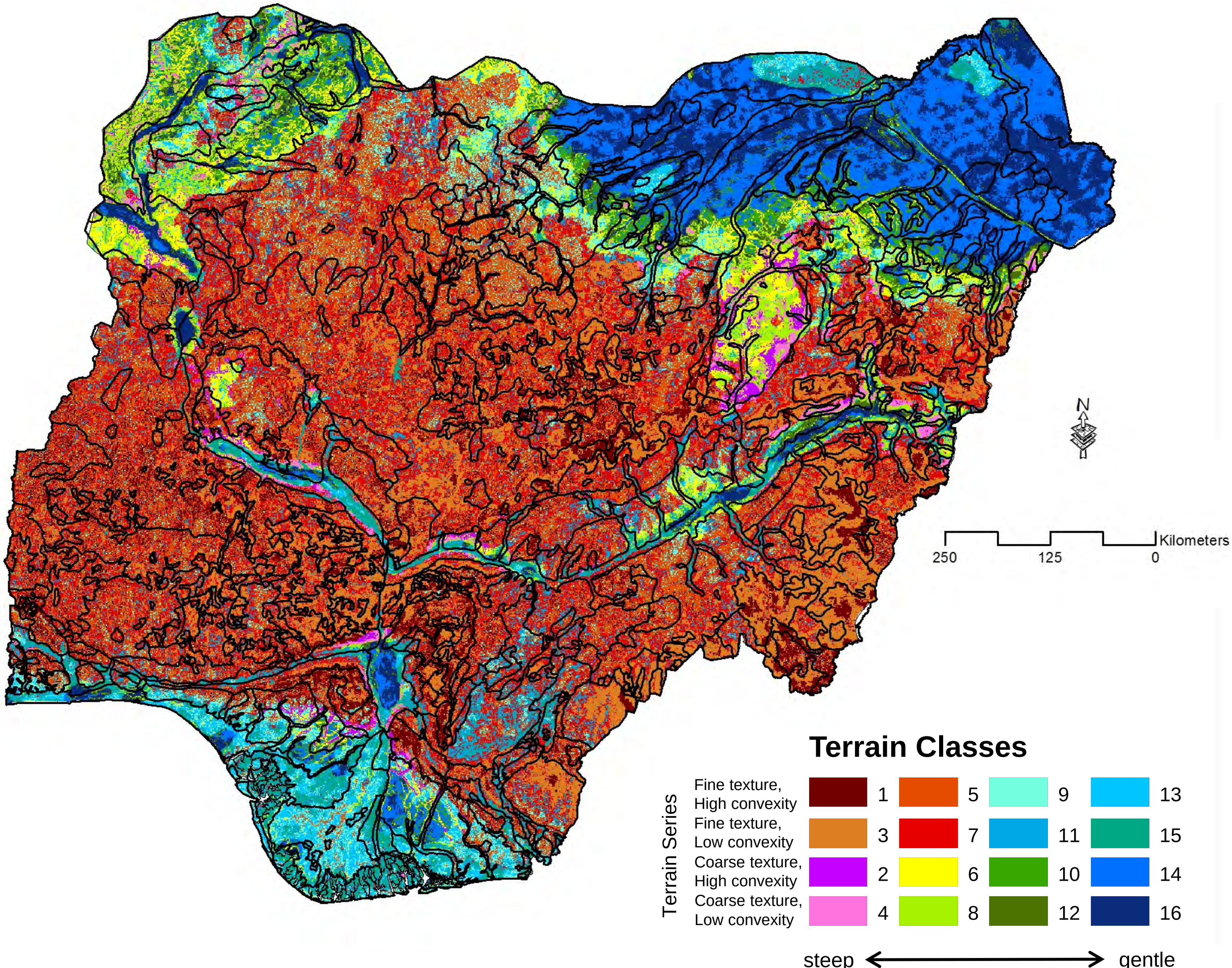
Global physiology



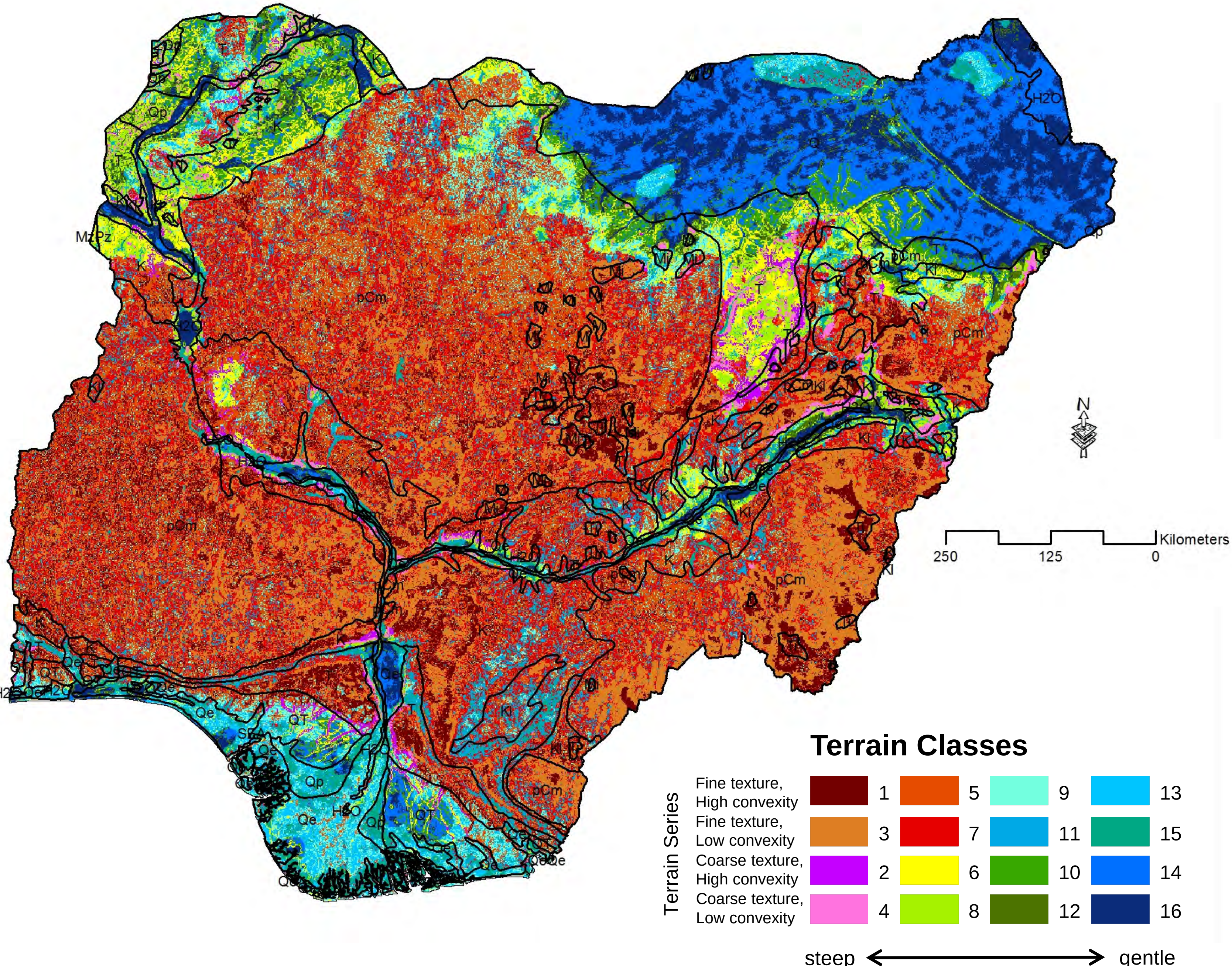
Iwahashi landform- slope, convexity & land surface texture



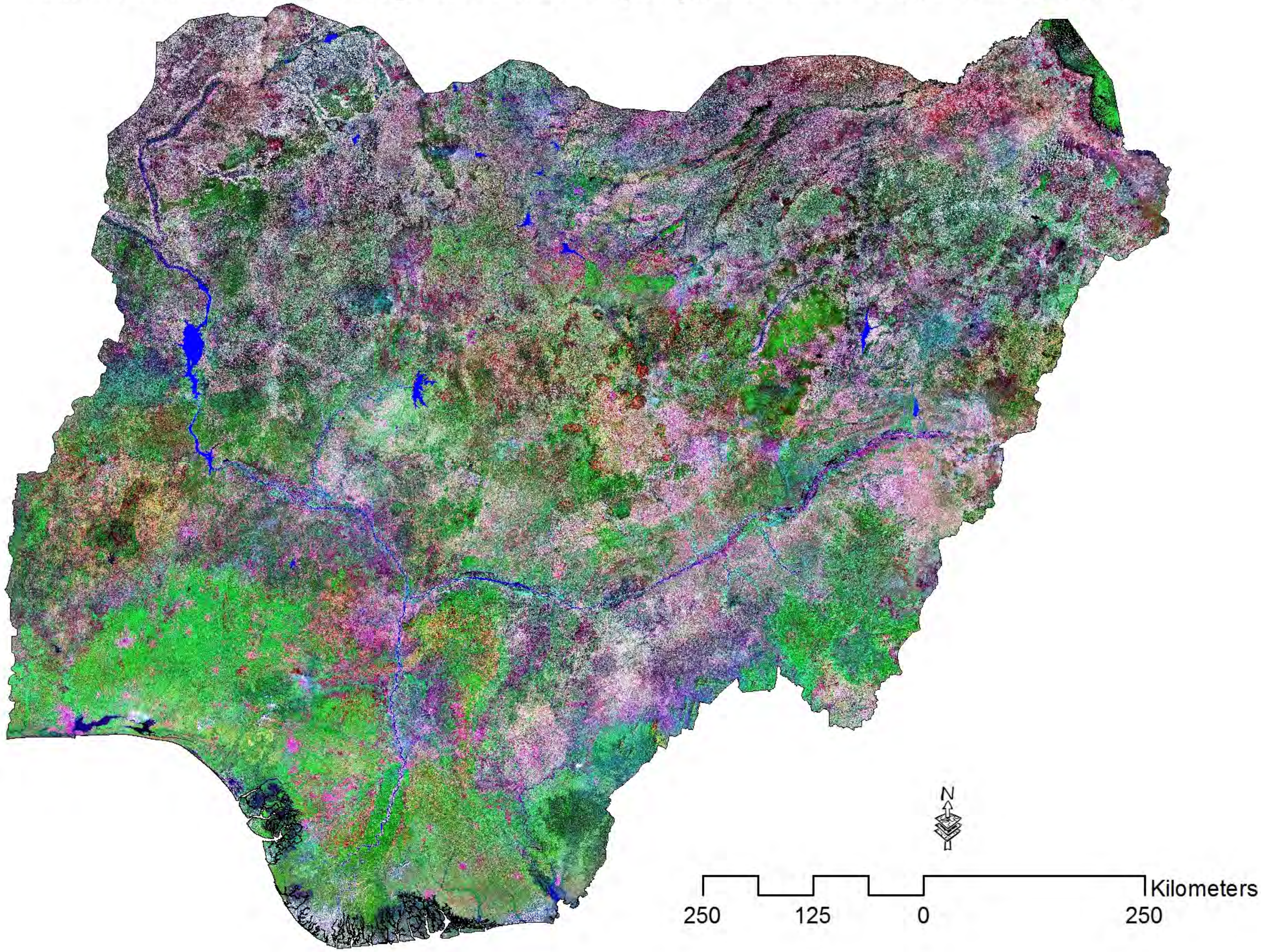
Iwahashi landform- overlain by soil



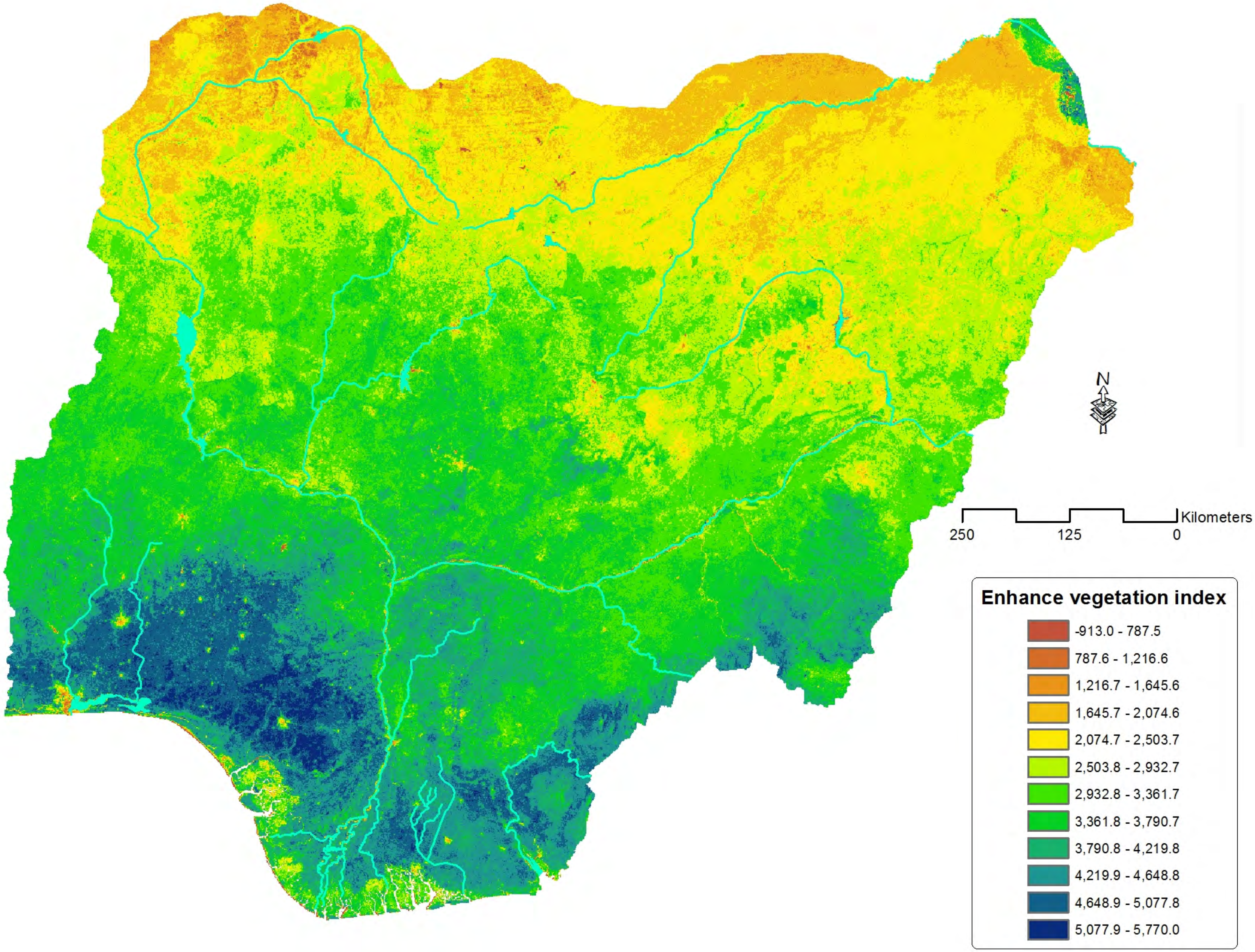
Iwahashi landform- overlain by geology



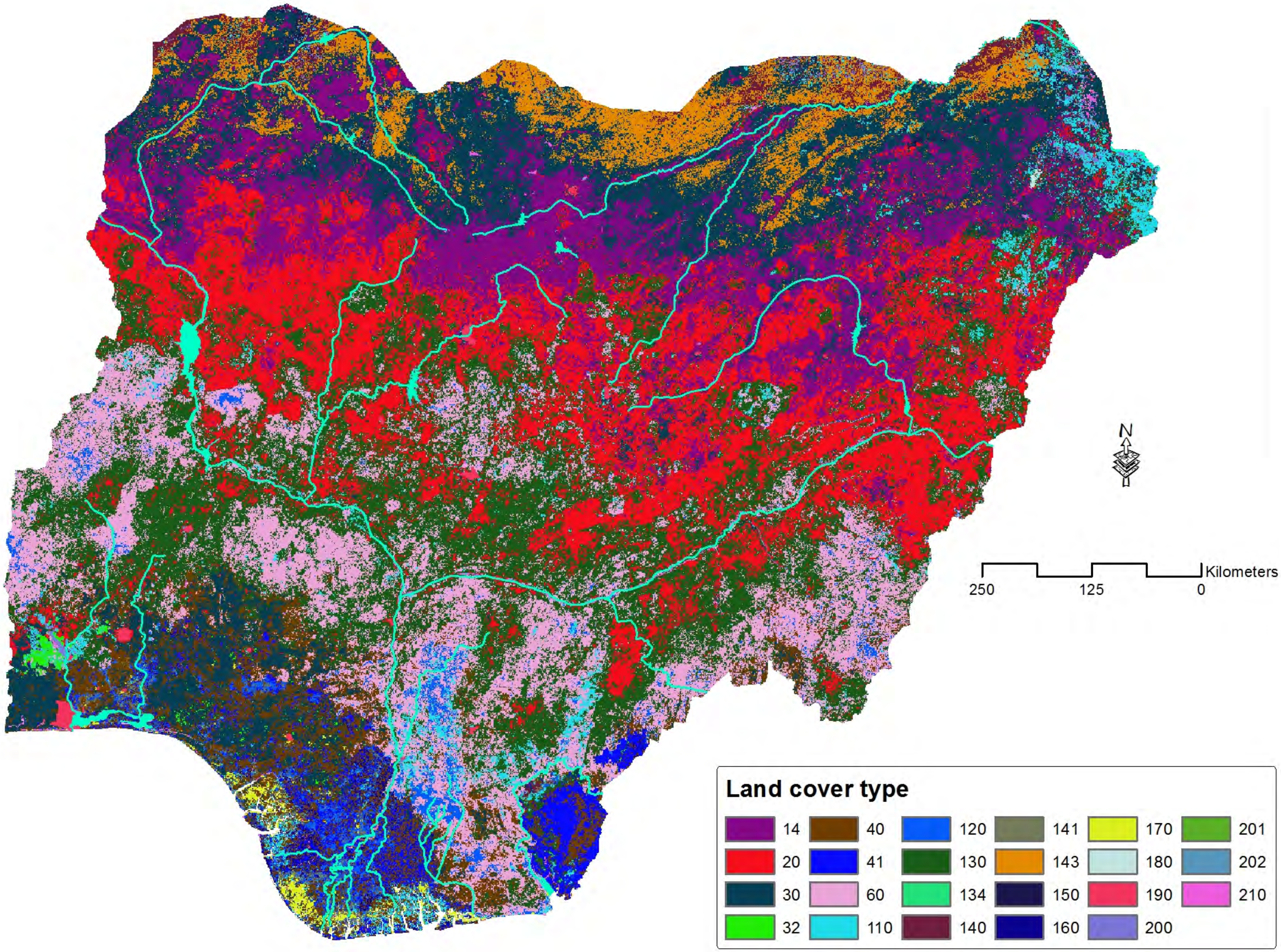
Landsat ETM 7 coverage of Nigeria- bands 2-4-7 (compiled from GlobalData/GeoCover2000)



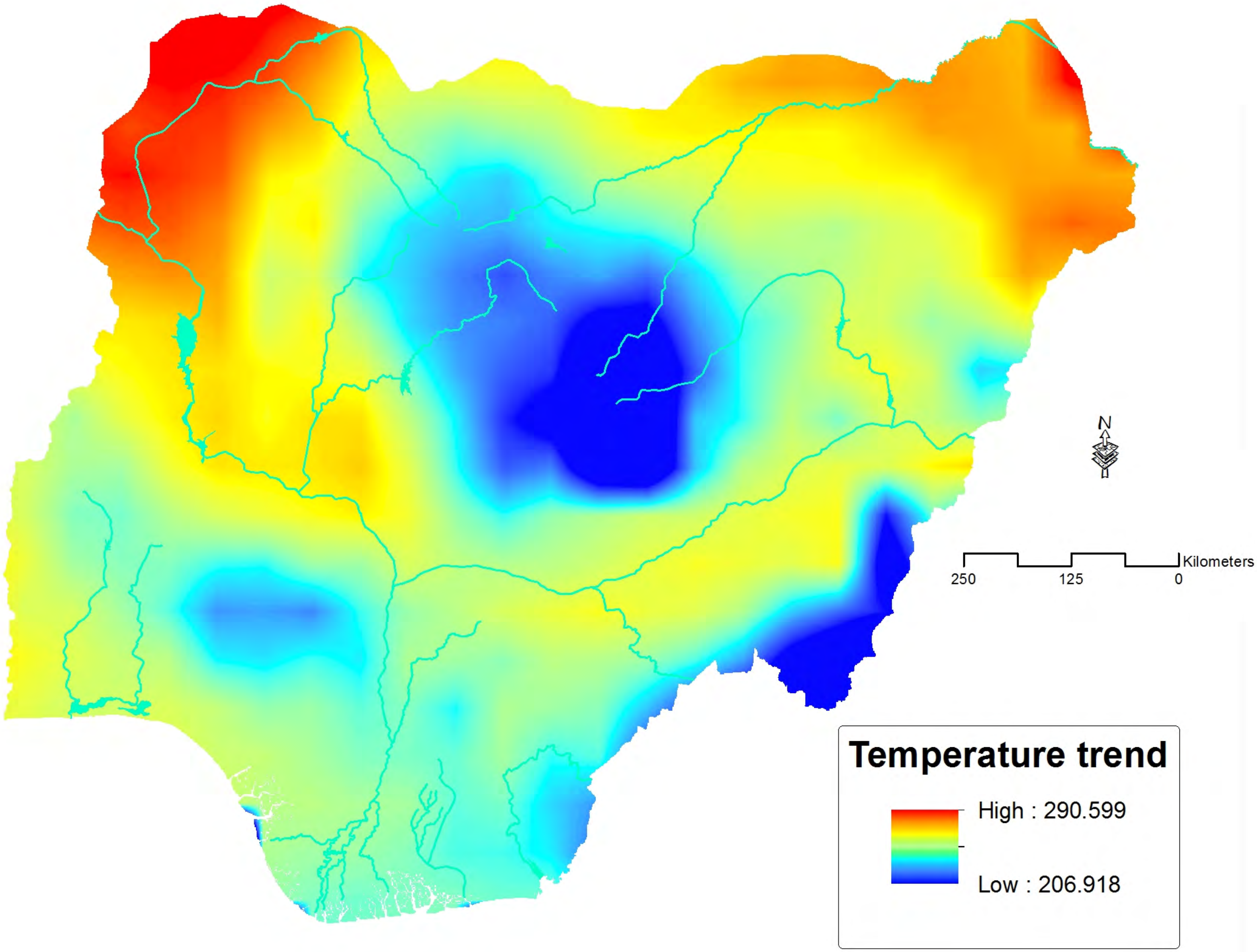
Enhanced vegetation index- from MODIS infrared/red bands



Land-cover types



Temperature- annual average



Modelling Methodology

Data archeology- locating and cataloguing of soil legacy data

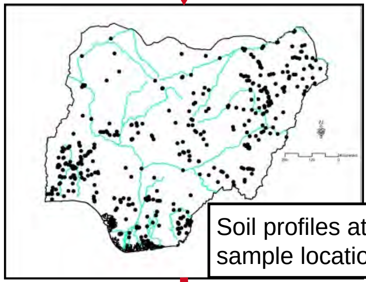
Data capture- scanning and digitisation of analogue soil legacy data

Acquisition and/or transformation of covariate data at fine (100m) grid

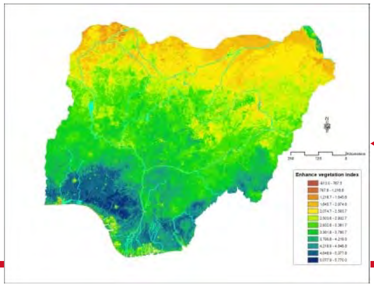
Data renewal- transformation of captured legacy data into usable digital database

Use data mining tool (Cubist) to interpolate a soil property at each depth onto the fine grid

$$V_d = f(Q) + e$$



Soil profiles at sample locations



Spline function- fit a spline function to each soil profile to estimate values at GSM standard depths

E.g., Digital map (100-m resolution) of a soil property at a given depth predicted from 572 locations and covariates

58

Modelling Methodology

Two modelling approaches exist:

- Spatial prediction (suitable for data-rich situations)
  - Geostatistics: REML-BLUP, BME
  - Statistical: MLR, GLM, GAM, etc.
  - Hybrid
- Data Mining tools (suitable data-scarce and/or complex situations)
  - Classification & Regression Trees
  - Neural Networks

Fundamental model for both approaches

That a soil property variability in space is a function of one or more covariates

$$V_d = f(Q) + e$$

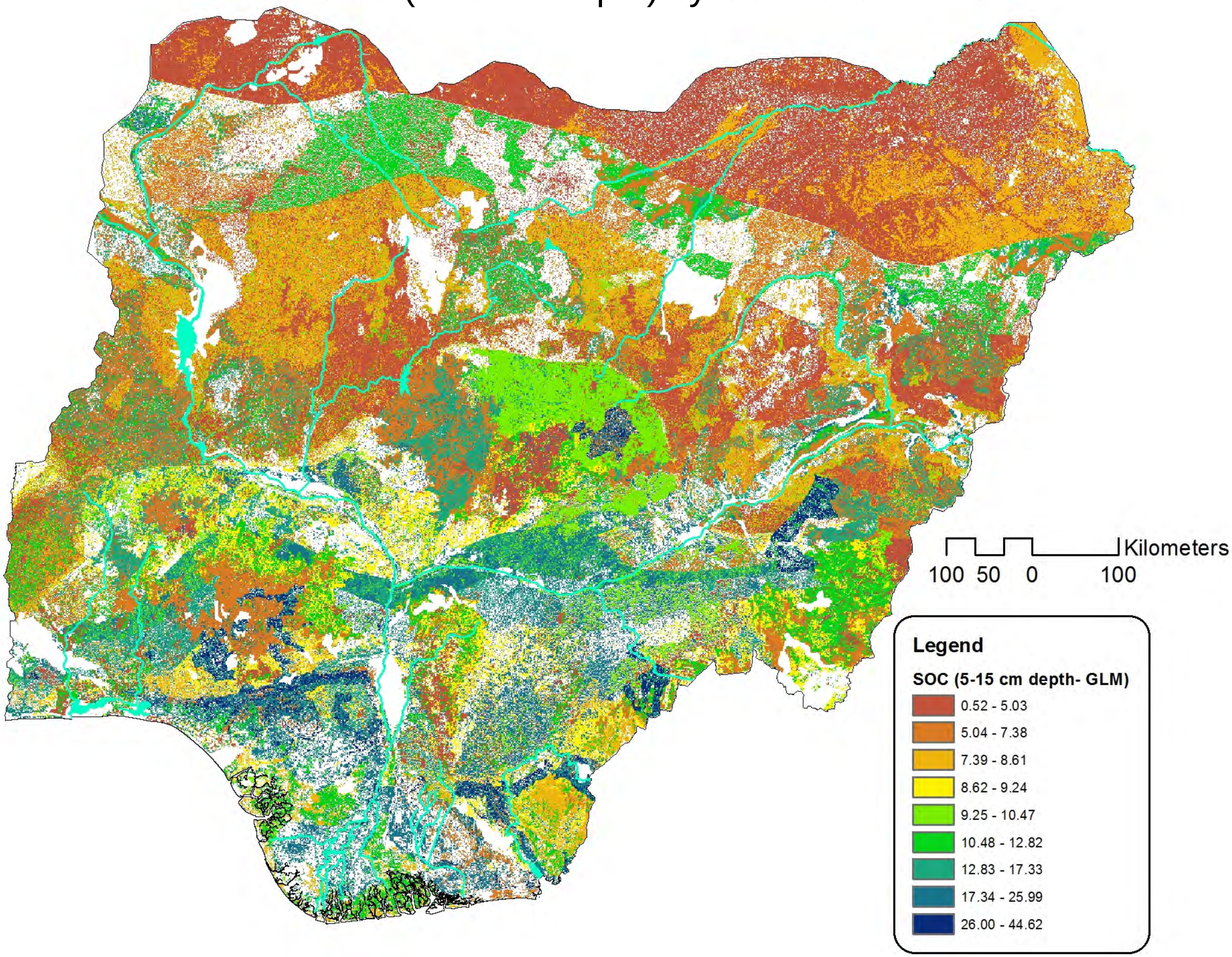
where V_d is the target soil property; Q is the matrix of covariates; e is the error term.

Modelling Methodology

We opted for regression tree model using cubist mining tool, because :

- Cubist is better amenable to extrapolation beyond the range of observed covariates at sample locations than GLM, neural network and classical regression tree model
- It is more robust for scarce data than other method- because it is able to exploit complex data structure by which it generates rules for modelling

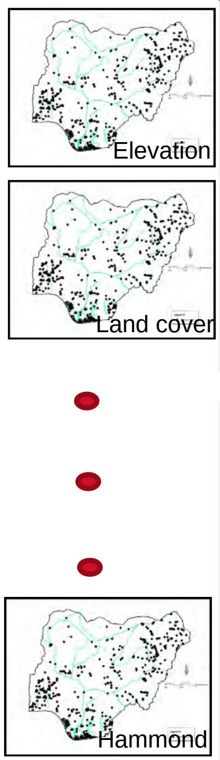
SOC (5-15 cm depth) by Generalised Linear Model



Using Regression Rules to Predict Soil Property From Covariates

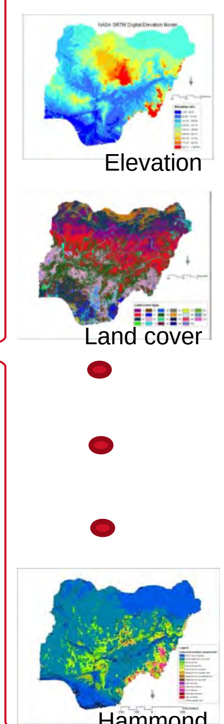
Use Cubist Machine Learning Tool to generate rules from values of a soil property (e.g., 0-5 cm pH) and covariates at 500-900 sample locations

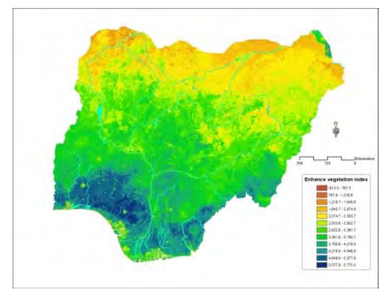
$$V_d = f\left\{ \cdots \right\} + e$$



Feed the rules into an ArcPython script to predict the soil property from the covariate raster data at 100-m resolution

$$f\left\{ \cdots \right\} =$$





E.g., Digital map of 0-5 cm depth soil pH at 100-m resolution

Using Regression Rules to Predict Soil Property From Covariates

Target attribute `pH05'

Use Cubist Machine Learning Tool to generate rules from values of a soil layer property (e.g., 0-5 cm pH) and of covariates (30 at 500 000 sample locations)

Feed the rules into an ArcPython script to predict the soil property from the covariate raster data sets at 100-m resolution;

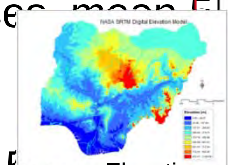
Read 876 cases (33 attributes) from ... data

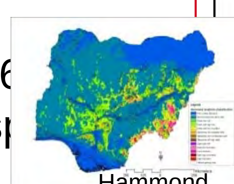
Model:

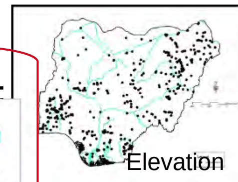
Rule 1: [374 cases, mean 5... 3.65 to 8.8, est err 0.590]

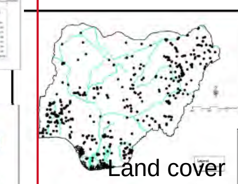
if
dem <= 288.5094
then
pH05 = 6.904 ... c - 0.068 wi
+ 0.002 ... 43 spi - 0.00...

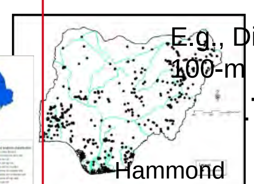
$f\ V_d =$ ... $=$

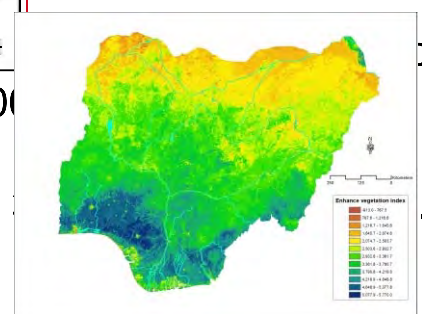










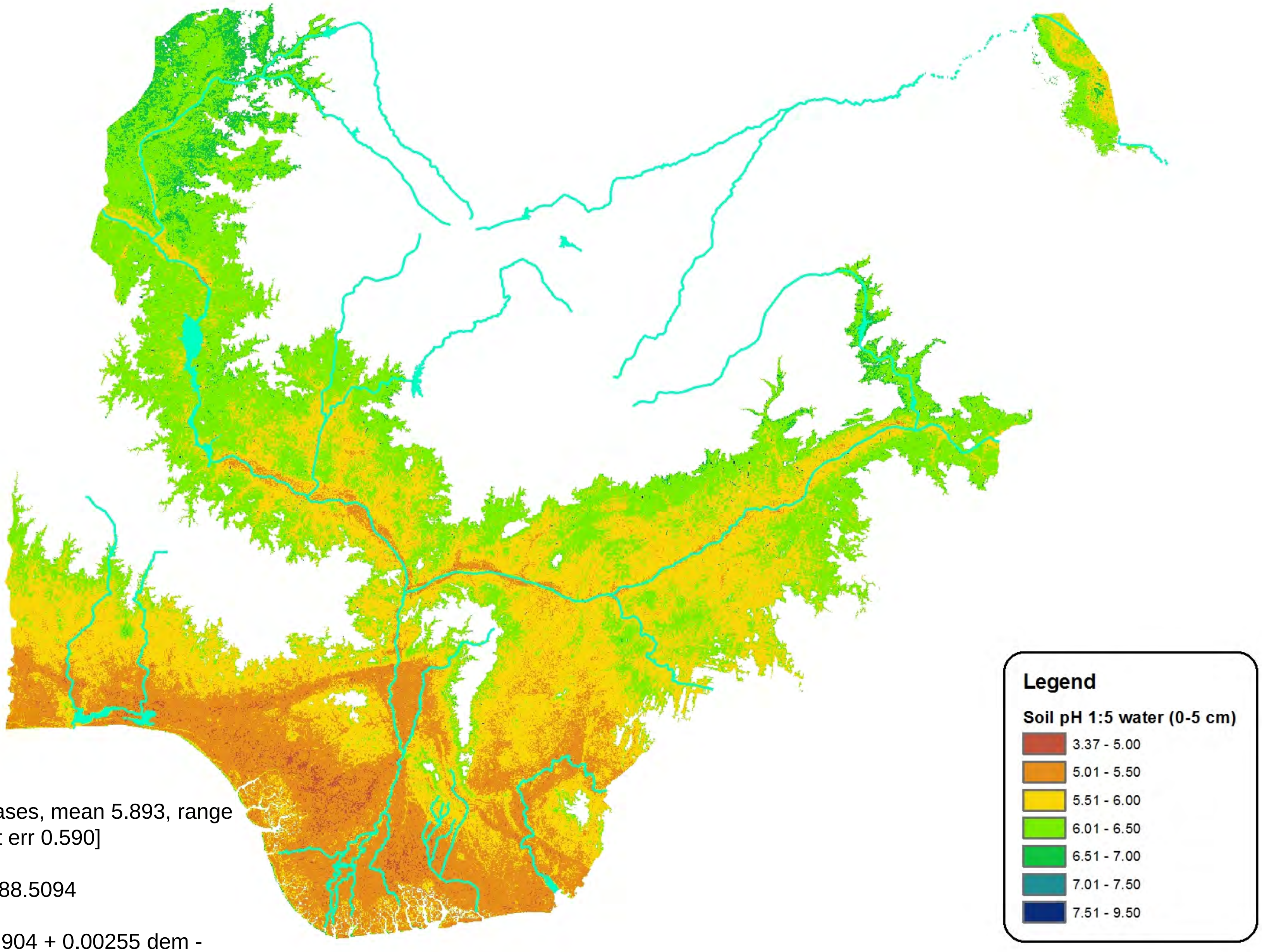


E.g., Digital map of soil pH (0-5 cm depth) at 100-m resolution

Rule 2: [502 cases, mean 6.388, range ... .632]

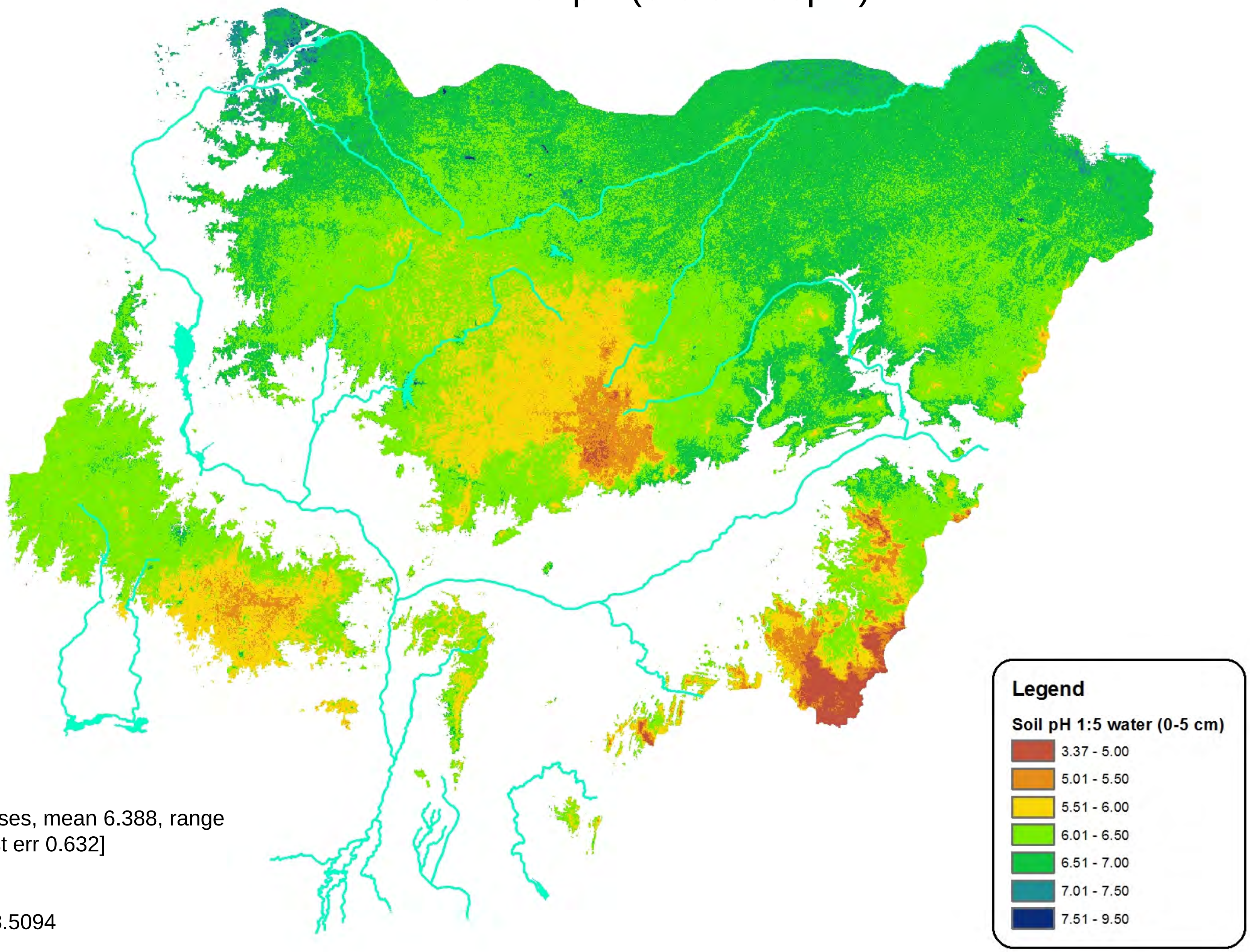
if
dem > 288.5094
then
pH05 = 8.796 ... 7 dem - 0.051 wi - 0.0013 lnsat4
+ 0.03 s...

Rule 1 for pH (0-5 cm depth)



Rule 1: [374 cases, mean 5.893, range 3.65 to 8.8, est err 0.590]
if
dem <= 288.5094
then
pH05 = 6.904 + 0.00255 dem - 0.0003 evi + 0.00036 flacc - 0.068 wi + 0.002 lnsat4 + 0.043 spi - 0.0012 lnsat7

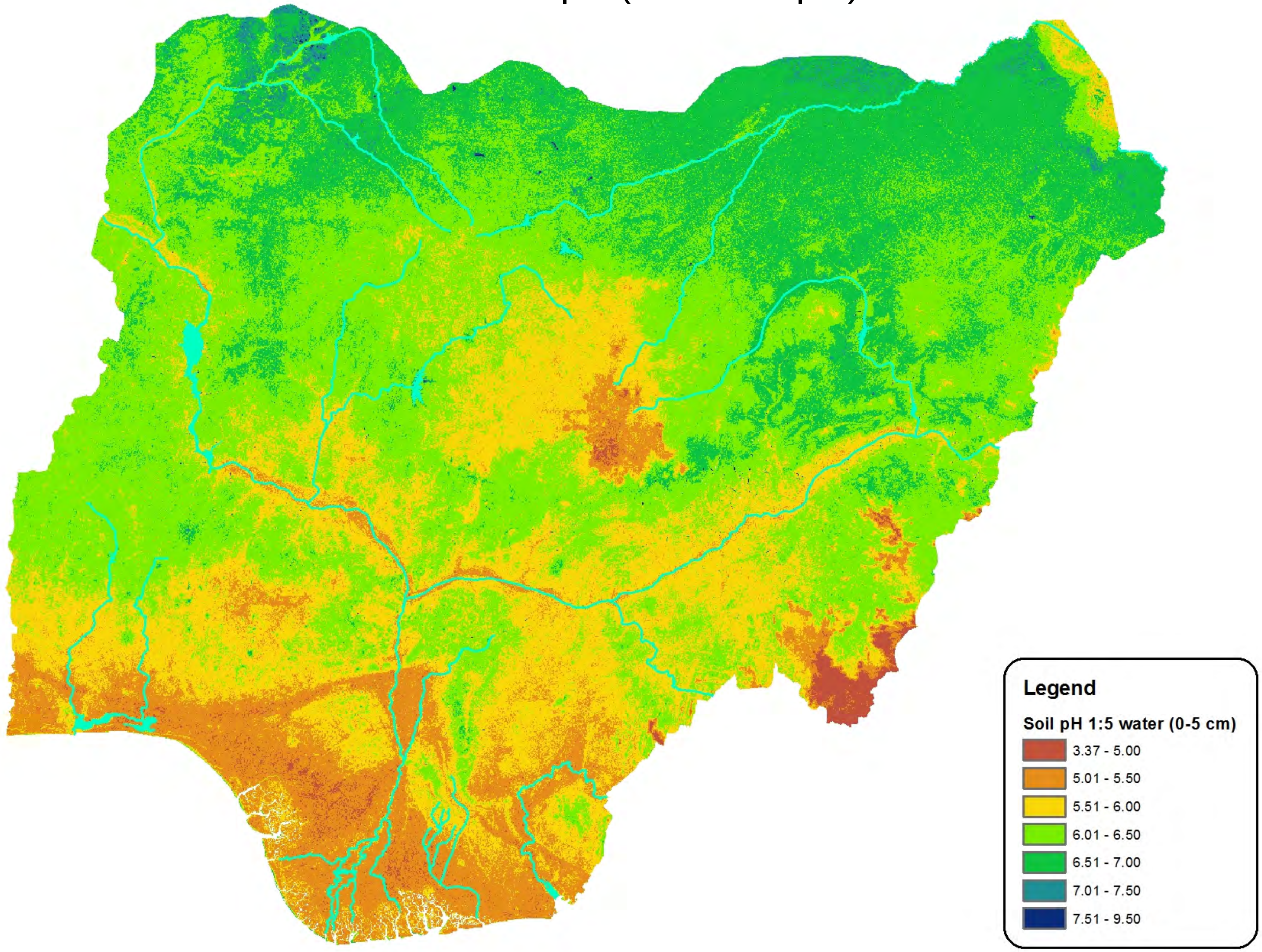
Rule 2 for pH (0-5 cm depth)



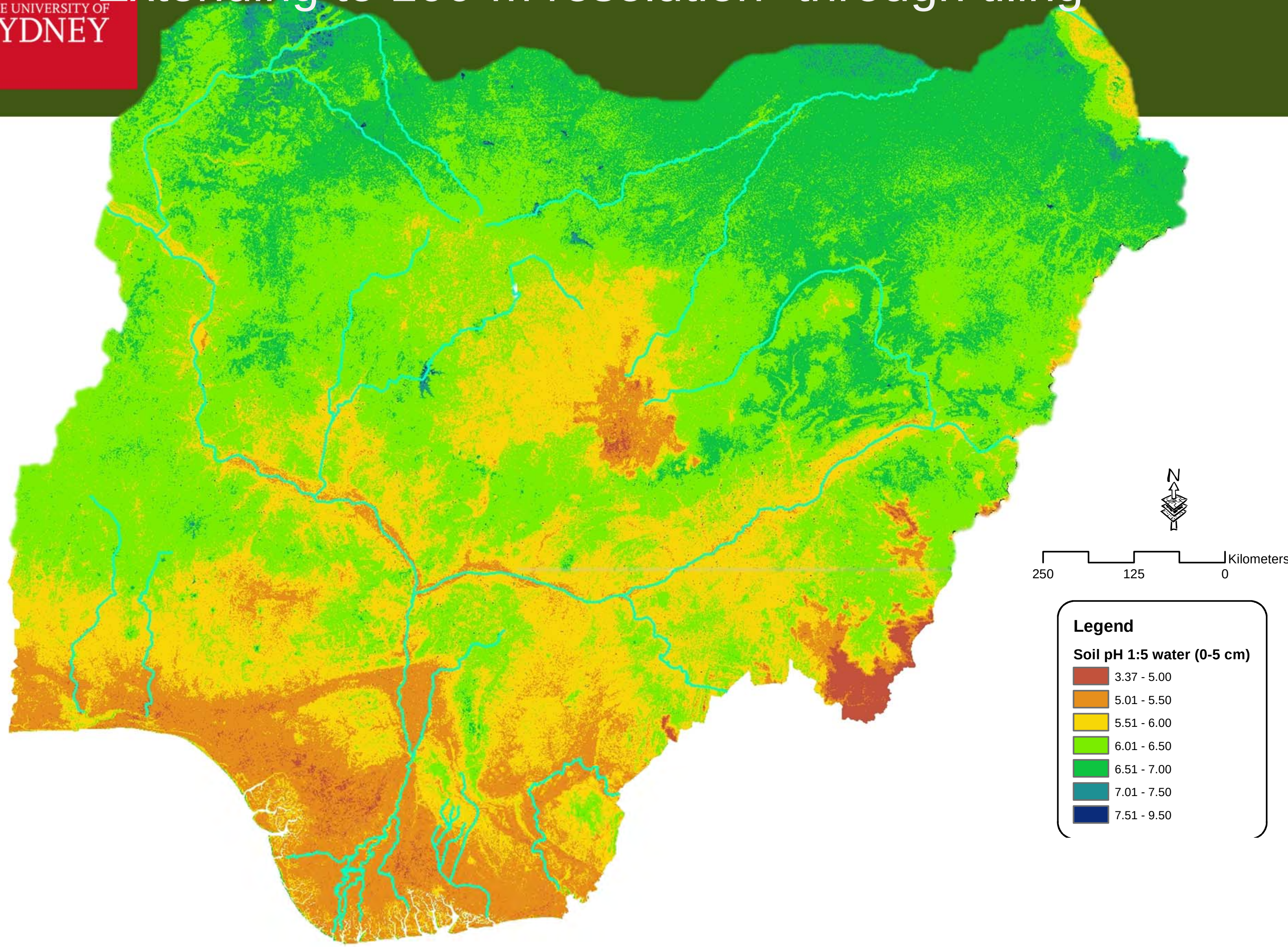
Rule 2: [502 cases, mean 6.388, range 3.61 to 9.43, est err 0.632]

if
dem > 288.5094
then
pH05 = 8.796 - 0.00042 evi - 0.00147 dem - 0.051 wi - 0.0013 lnsat4 + 0.03 spi

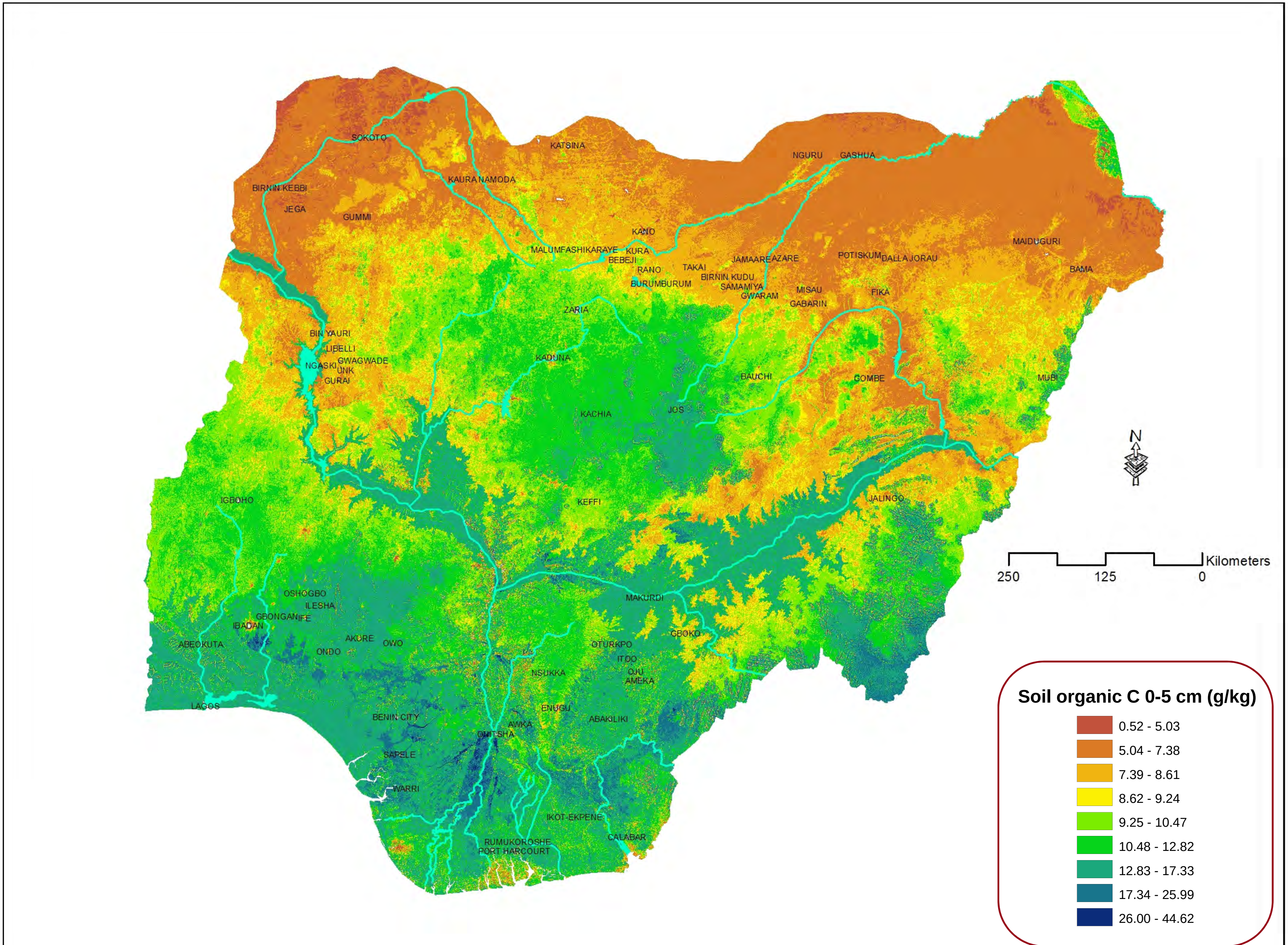
Rules 1 & 2 for pH (0-5 cm depth)- mosaicked



Extending to 100-m resolution- through tiling



Results for Soil Organic Carbon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BAMA
BURUMBURUM
BIRNIN KUDU
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KEFFI
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Kilometers
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BENIN CITY
ABAKILIKI
AWKA
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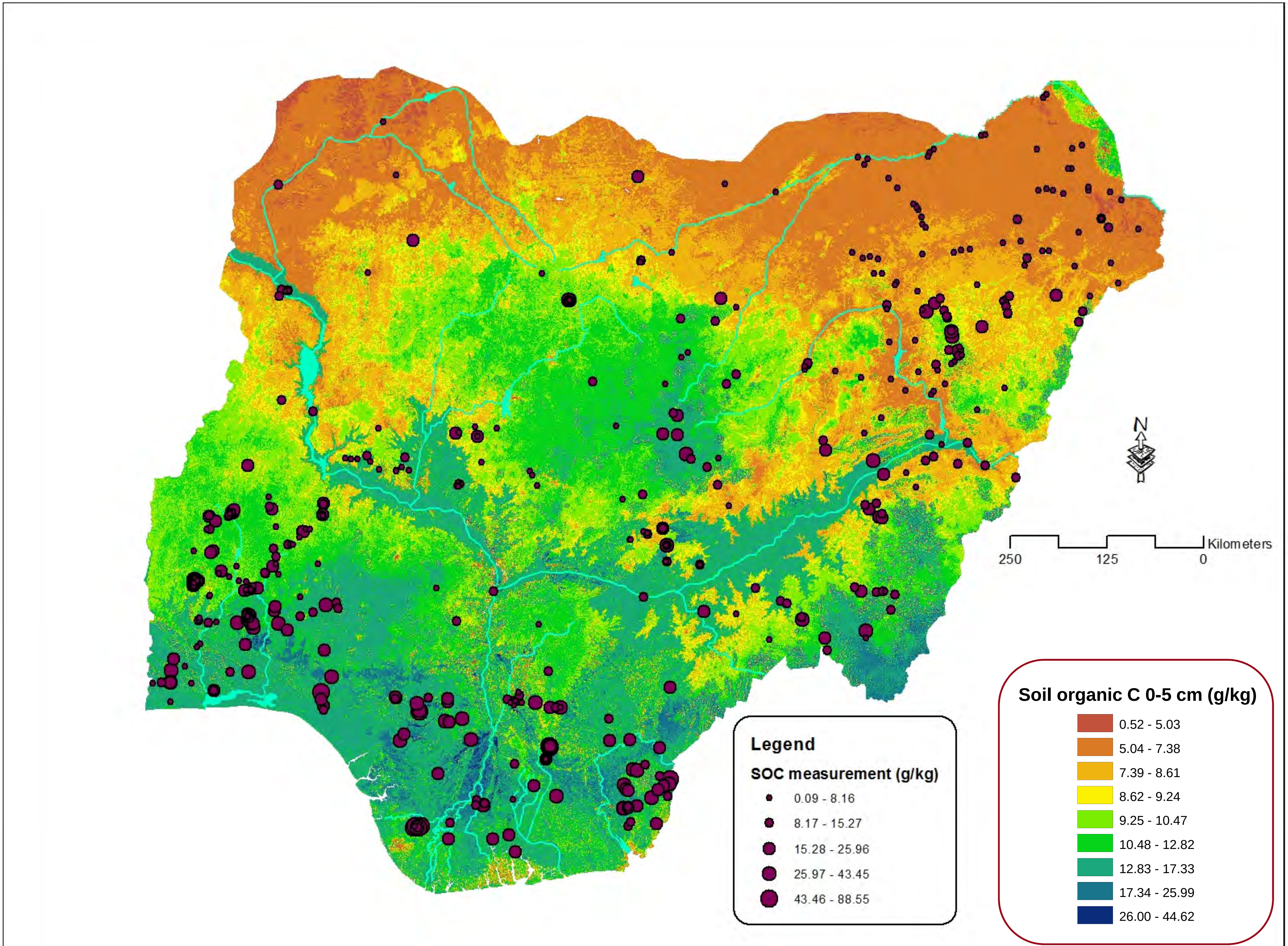
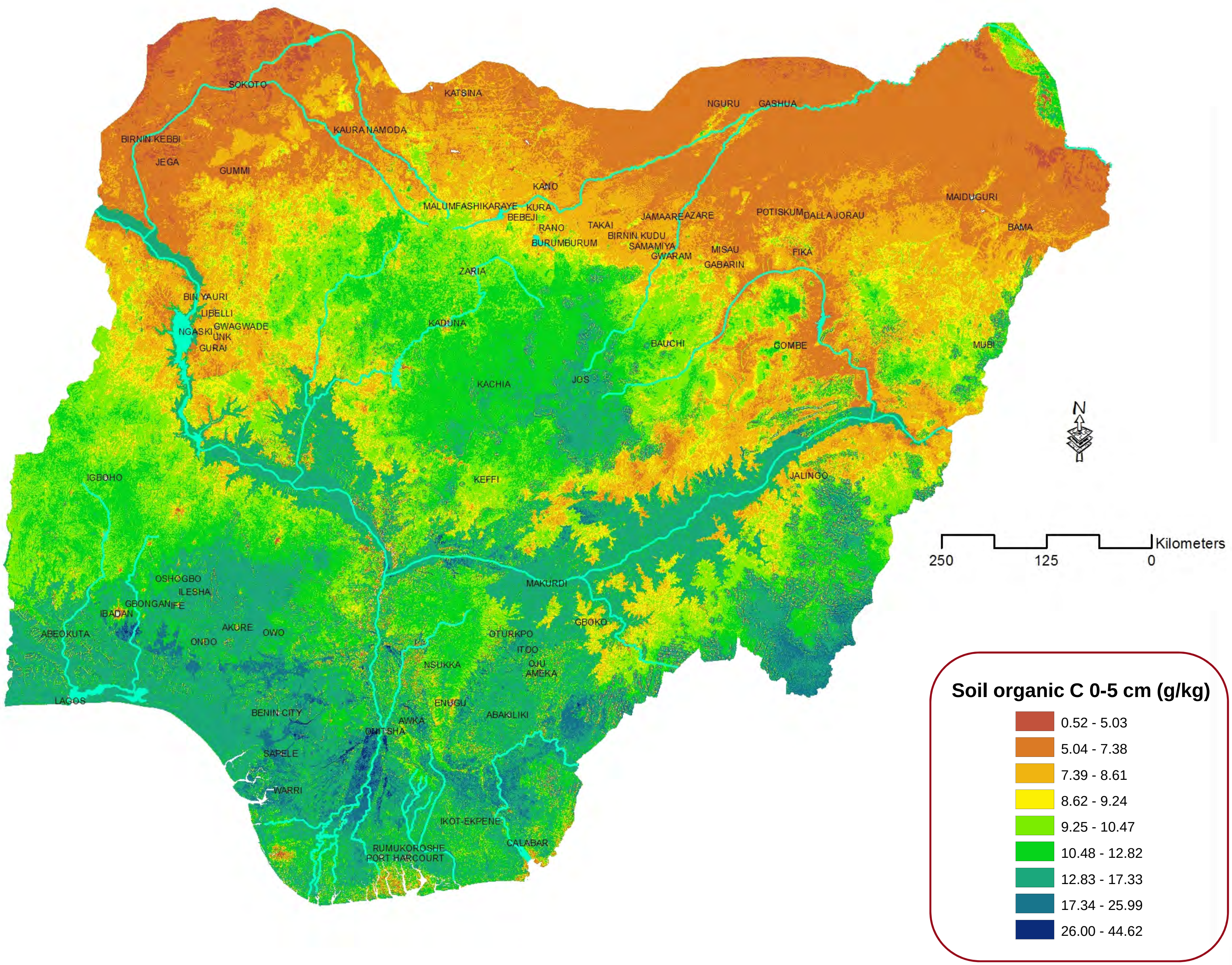
WARRI
IKOT-EKPENE
CALABAR
RUMUKOROSHE
PORT HARCOURT
Soil organic C 0-5 cm (g/kg)
0.52 - 5.03
5.04 - 7.38
7.39 - 8.61
8.62 - 9.24
9.25 - 10.47
10.48 - 12.82
12.83 - 17.33
17.34 - 25.99
26.00 - 44.62


N
250
125
0
Kilometers
Legend
SOC measurement (g/kg)
0.09 - 8.16
8.17 - 15.27
15.28 - 25.96
25.97 - 43.45
43.46 - 88.55
Soil organic C 0-5 cm (g/kg)
0.52 - 5.03
5.04 - 7.38
7.39 - 8.61
8.62 - 9.24
9.25 - 10.47
10.48 - 12.82
12.83 - 17.33
17.34 - 25.99
26.00 - 44.62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Kilometers
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Soil organic C 0-5 cm (g/kg)
0.52 - 5.03
5.04 - 7.38
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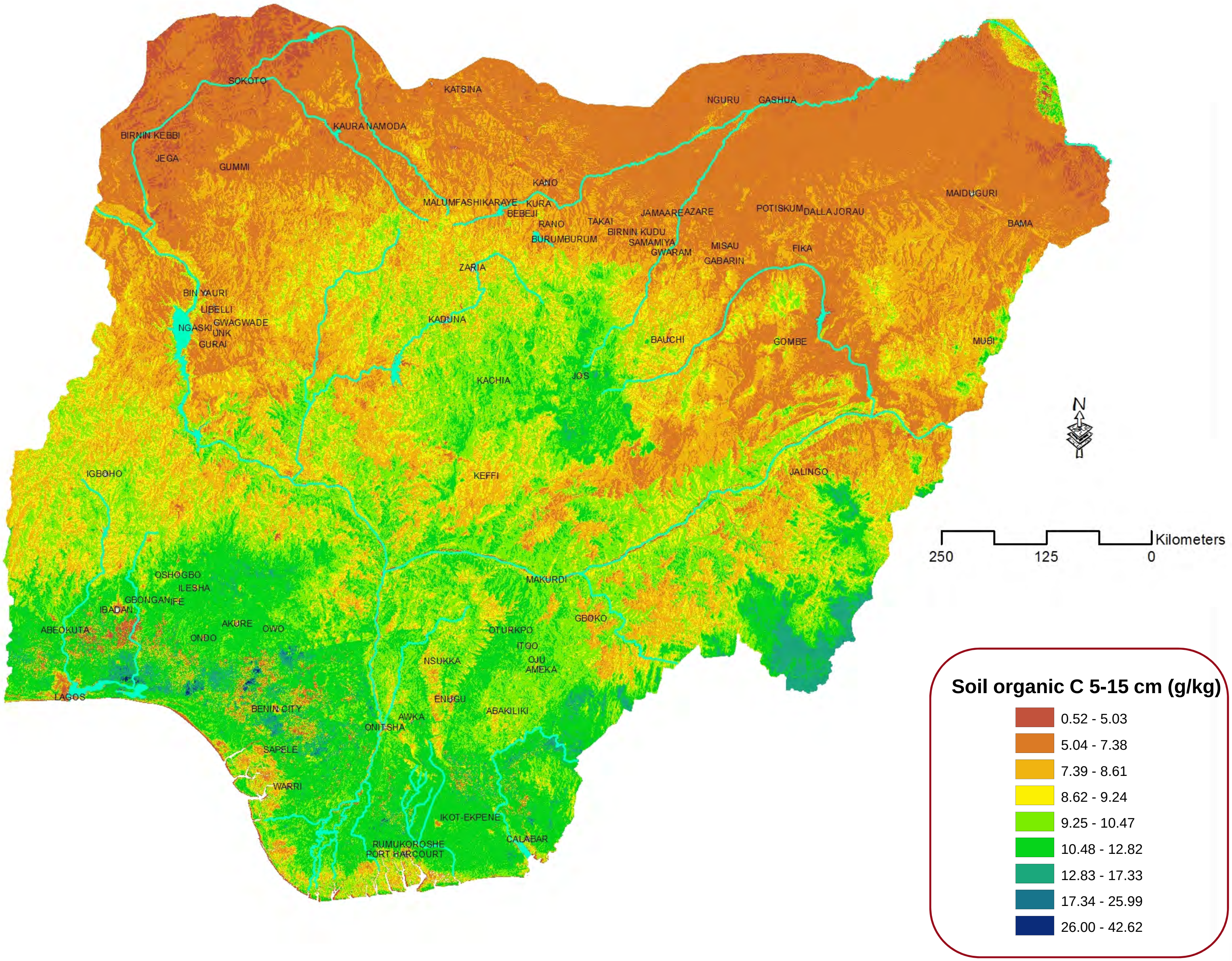
8.62 - 9.24
9.25 - 10.47
10.48 - 12.82
12.83 - 17.33
17.34 - 25.99
26.00 - 44.62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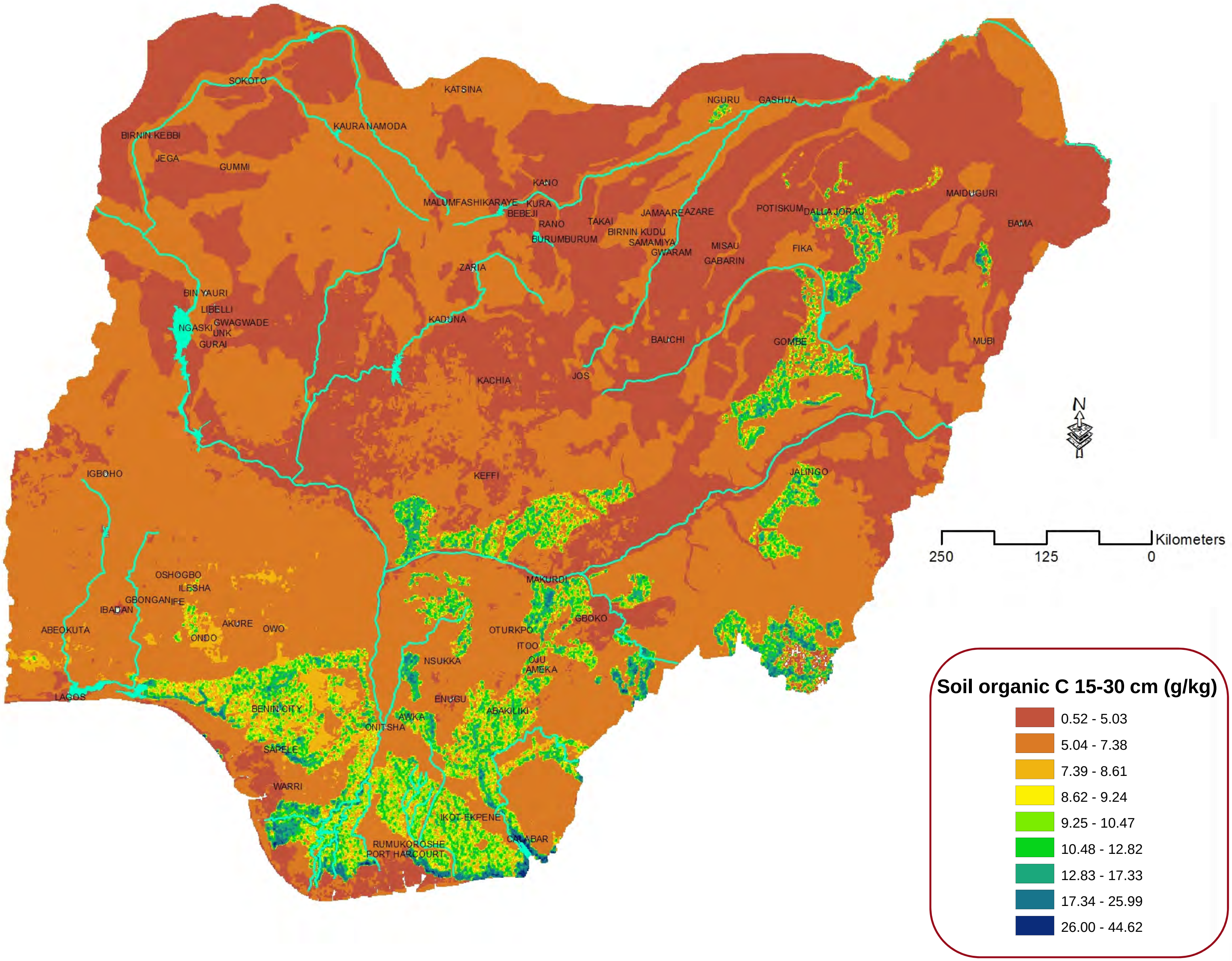
WARRI
IKOT-EKPENE
CALABAR
RUMUKOROSHE
PORT HARCOURT
N
250
125
0
Kilometers
Soil organic C 5-15 cm (g/kg)
0.52 - 5.03
5.04 - 7.38
7.39 - 8.61
8.62 - 9.24
9.25 - 10.47
10.48 - 12.82
12.83 - 17.33
17.34 - 25.99
26.00 - 42.62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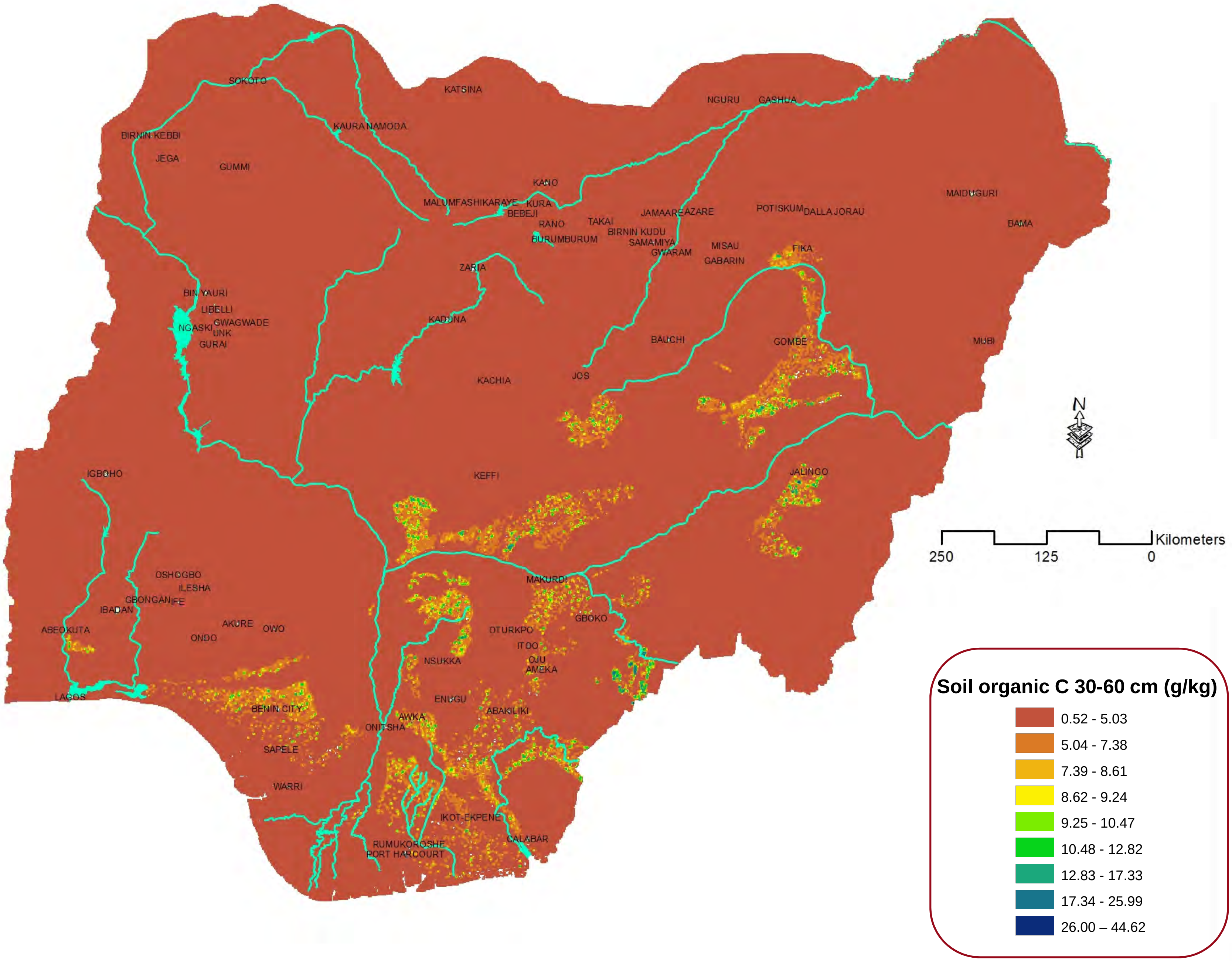
WARRI
IKOT-EKPENE
RUMUKOROSHE
PORT HARCOURT
CALABAR
N
250
125
0
Kilometers
Soil organic C 15-30 cm (g/kg)
0.52 - 5.03
5.04 - 7.38
7.39 - 8.61
8.62 - 9.24
9.25 - 10.47
10.48 - 12.82
12.83 - 17.33
17.34 - 25.99
26.00 - 44.62


Soil organic C 30-60 cm (g/kg)
0.52 - 5.03
5.04 - 7.38
7.39 - 8.61
8.62 - 9.24
9.25 - 10.47
10.48 - 12.82
12.83 - 17.33
17.34 - 25.99
26.00 – 44.62
N
250
125
0
Kilometers
SOKOTO
KATSINA
KAURA NAMODA
BIRNIN KEBBI
JEGA
GUMMI
NGURU
GASHUA
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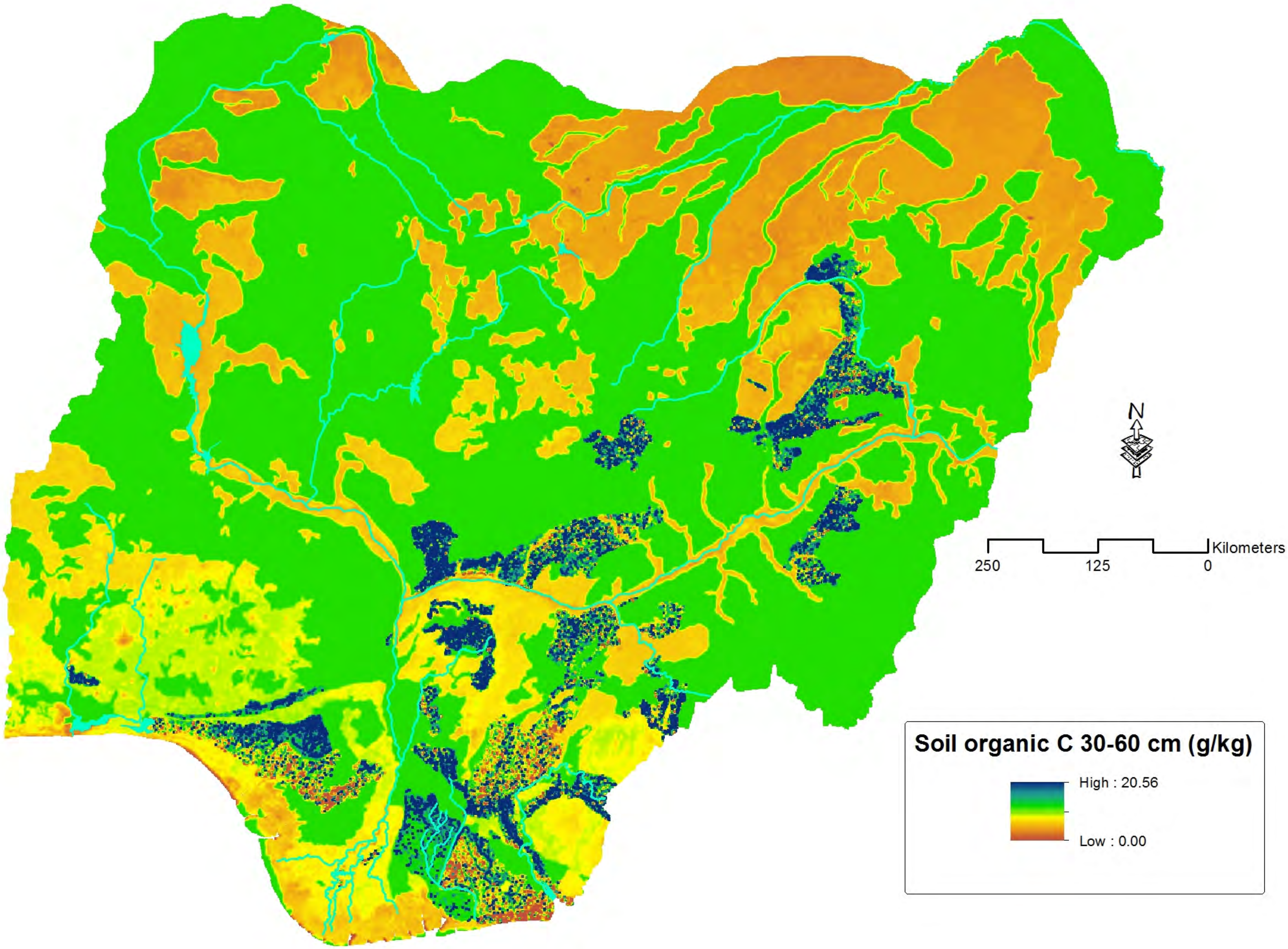
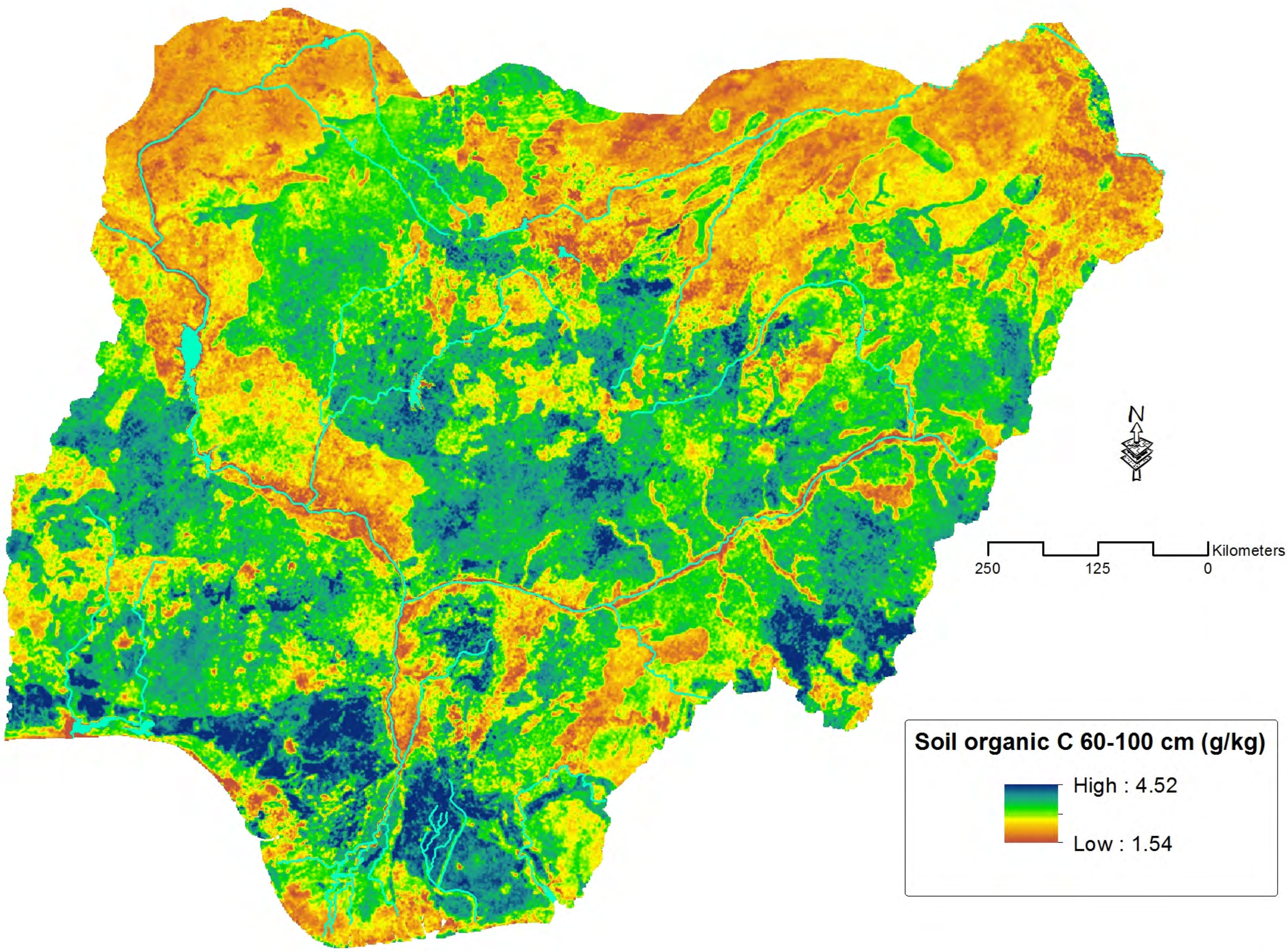
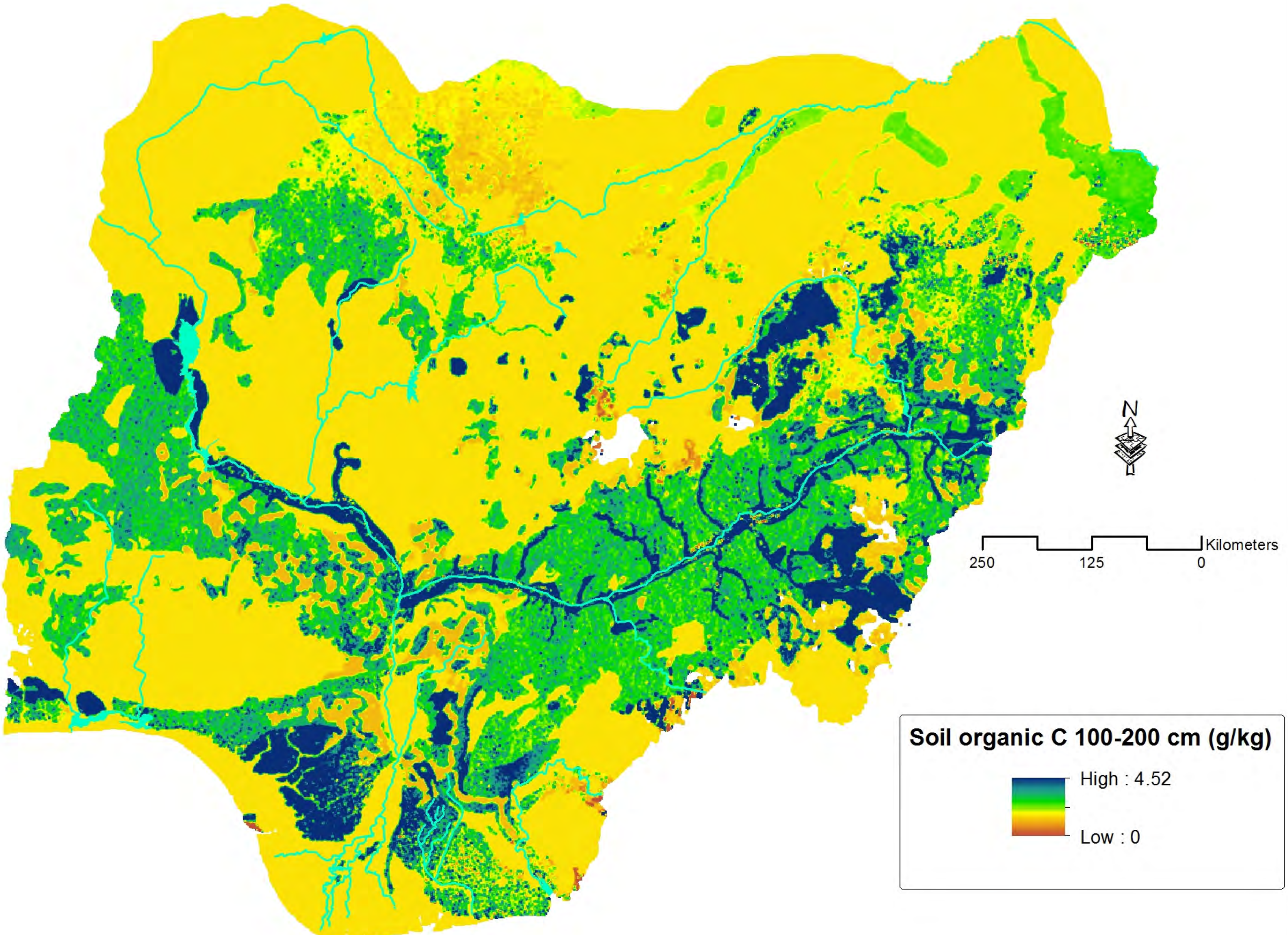
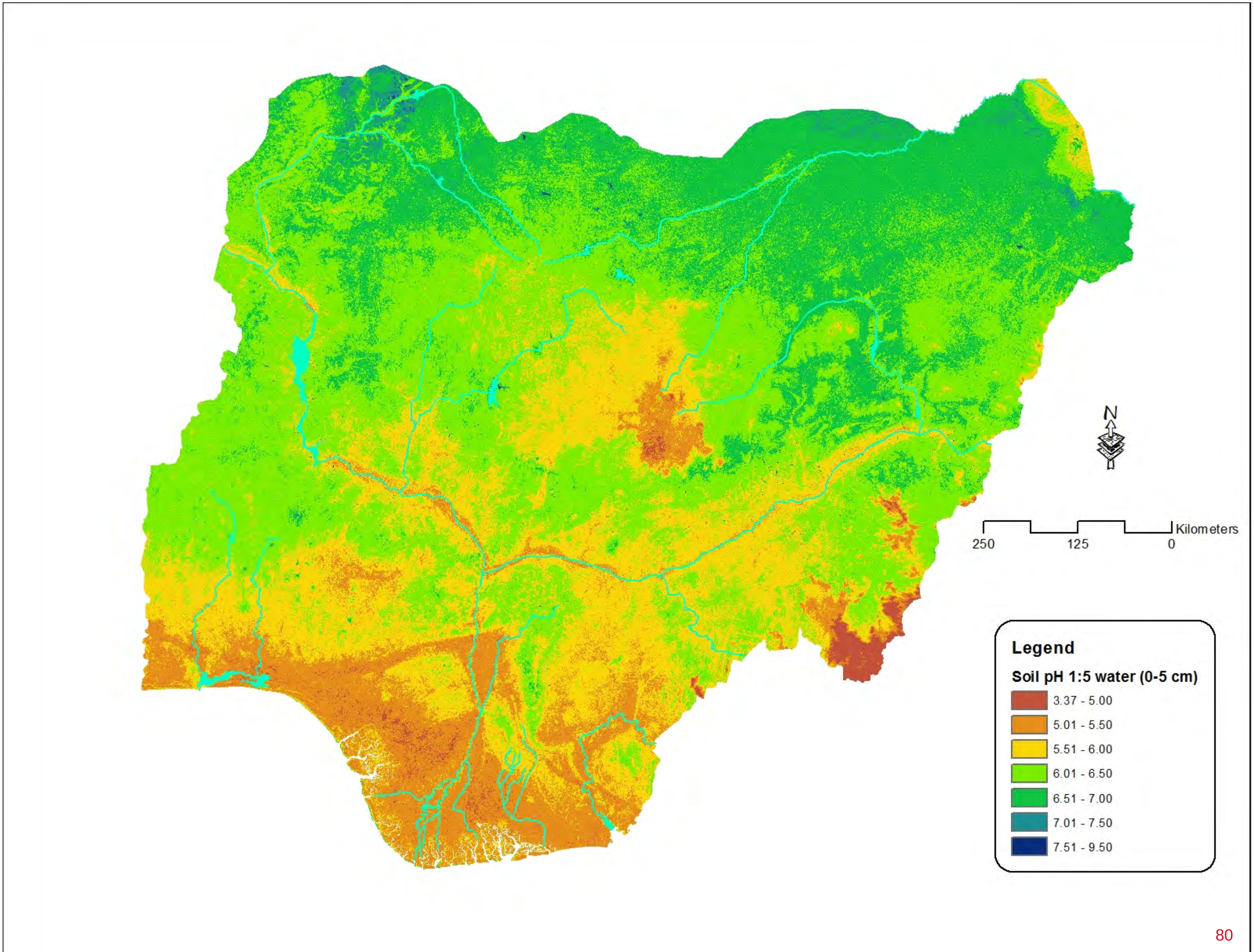
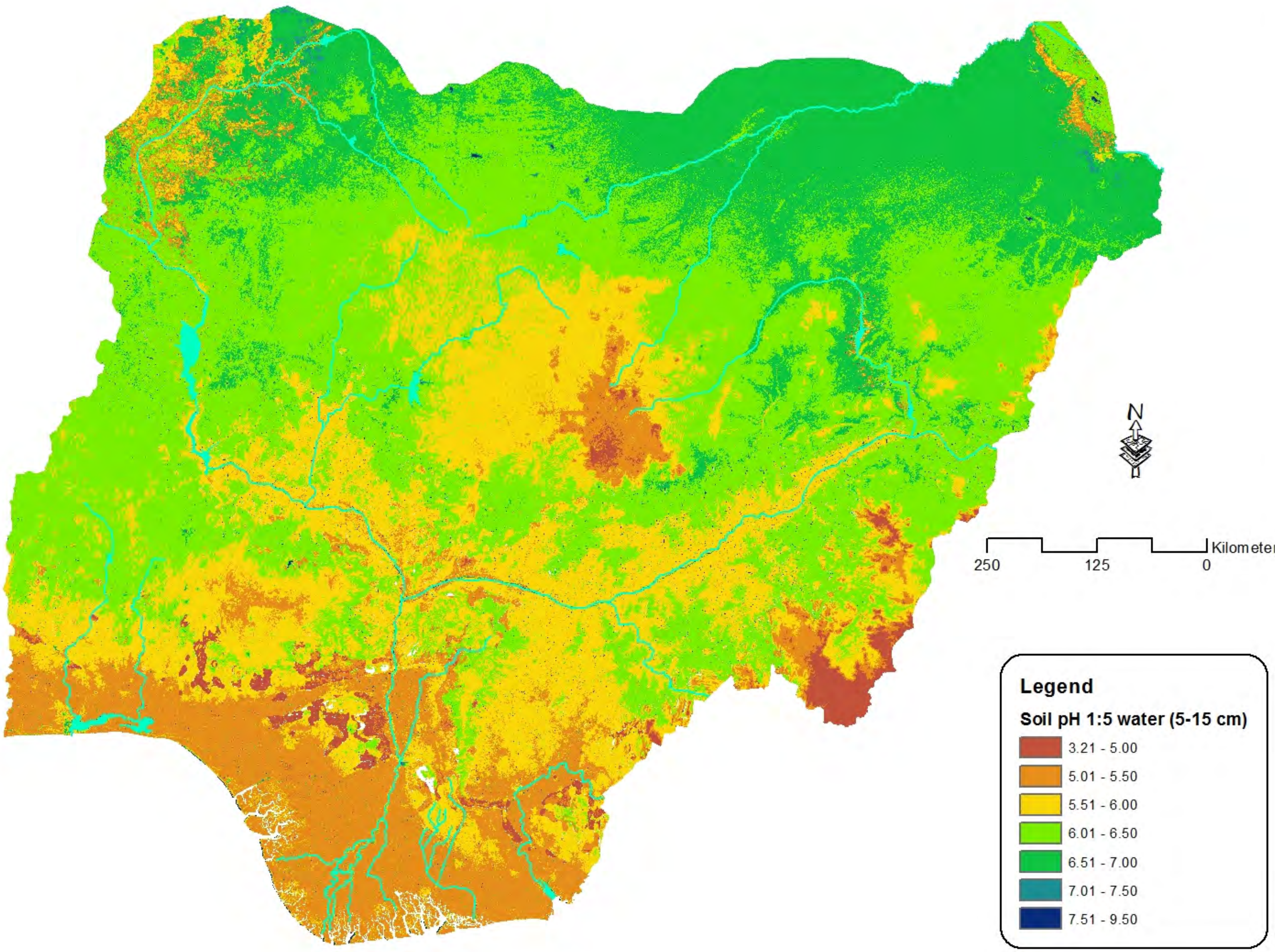

N
250
125
0
Kilometers
Soil organic C 30-60 cm (g/kg)
High : 20.56
Low : 0.00

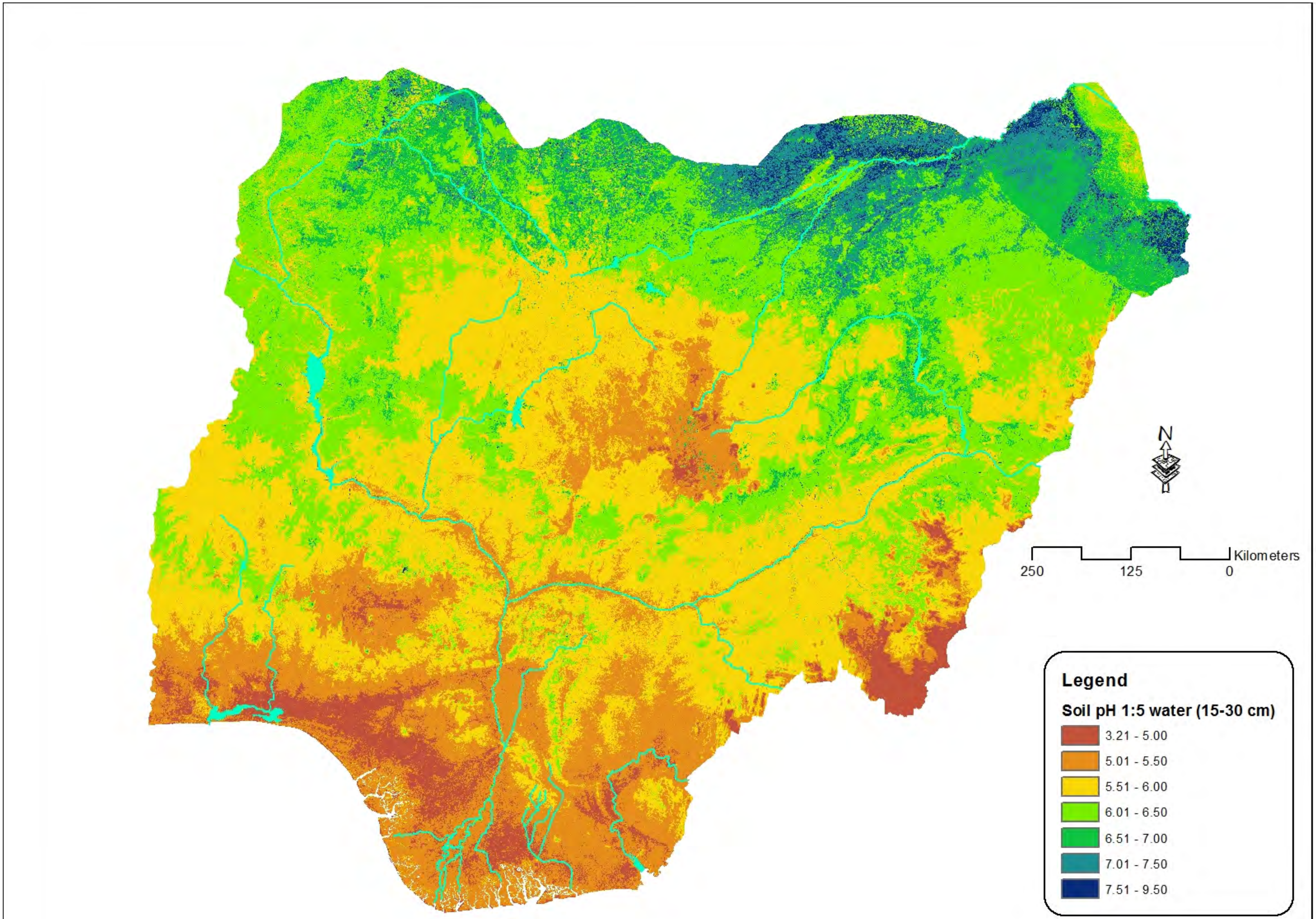

N
Kilometers
250
125
0
Soil organic C 60-100 cm (g/kg)
High : 4.52
Low : 1.54

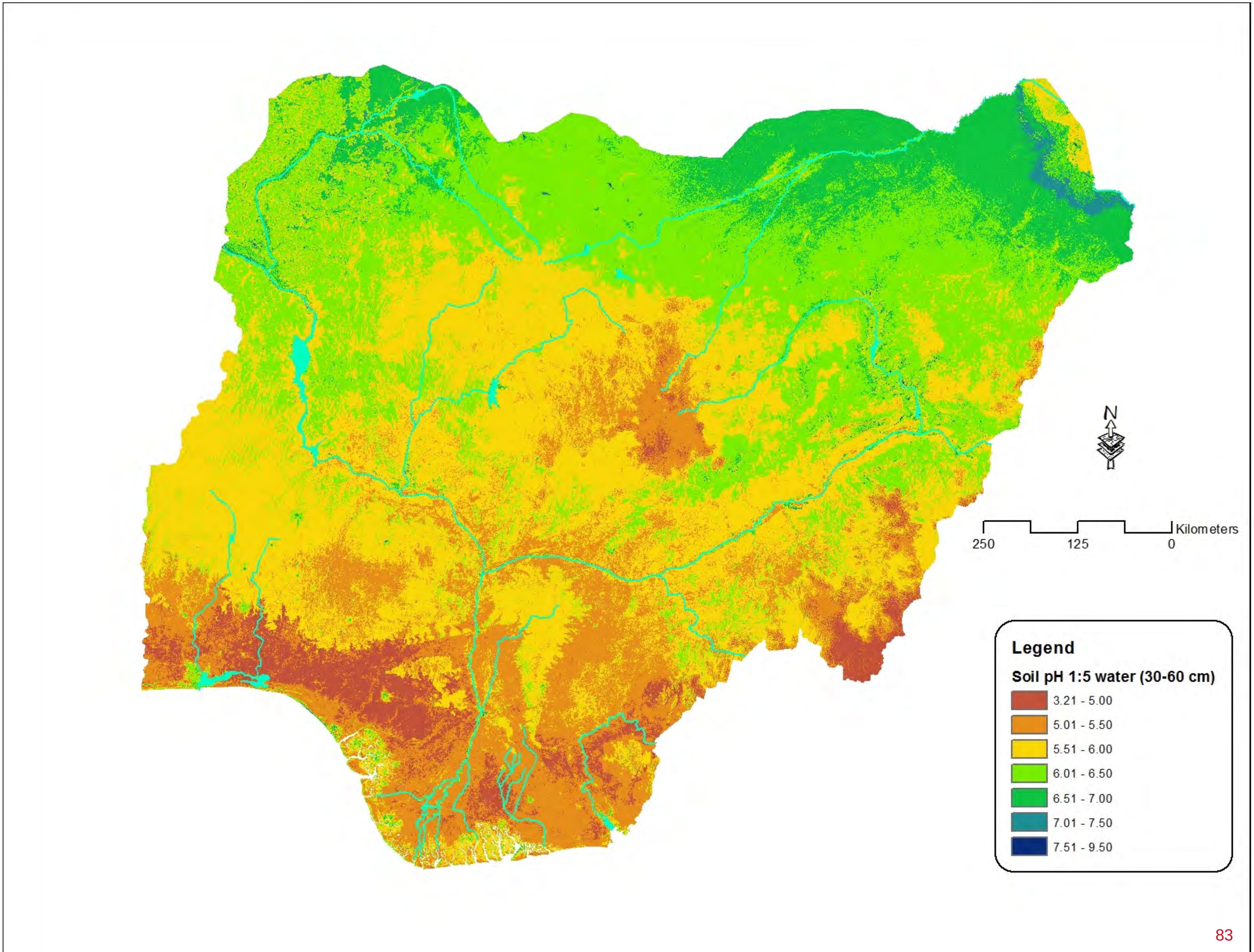

N
250
125
0
Kilometers
Soil organic C 100-200 cm (g/kg)
High : 4.52
Low : 0

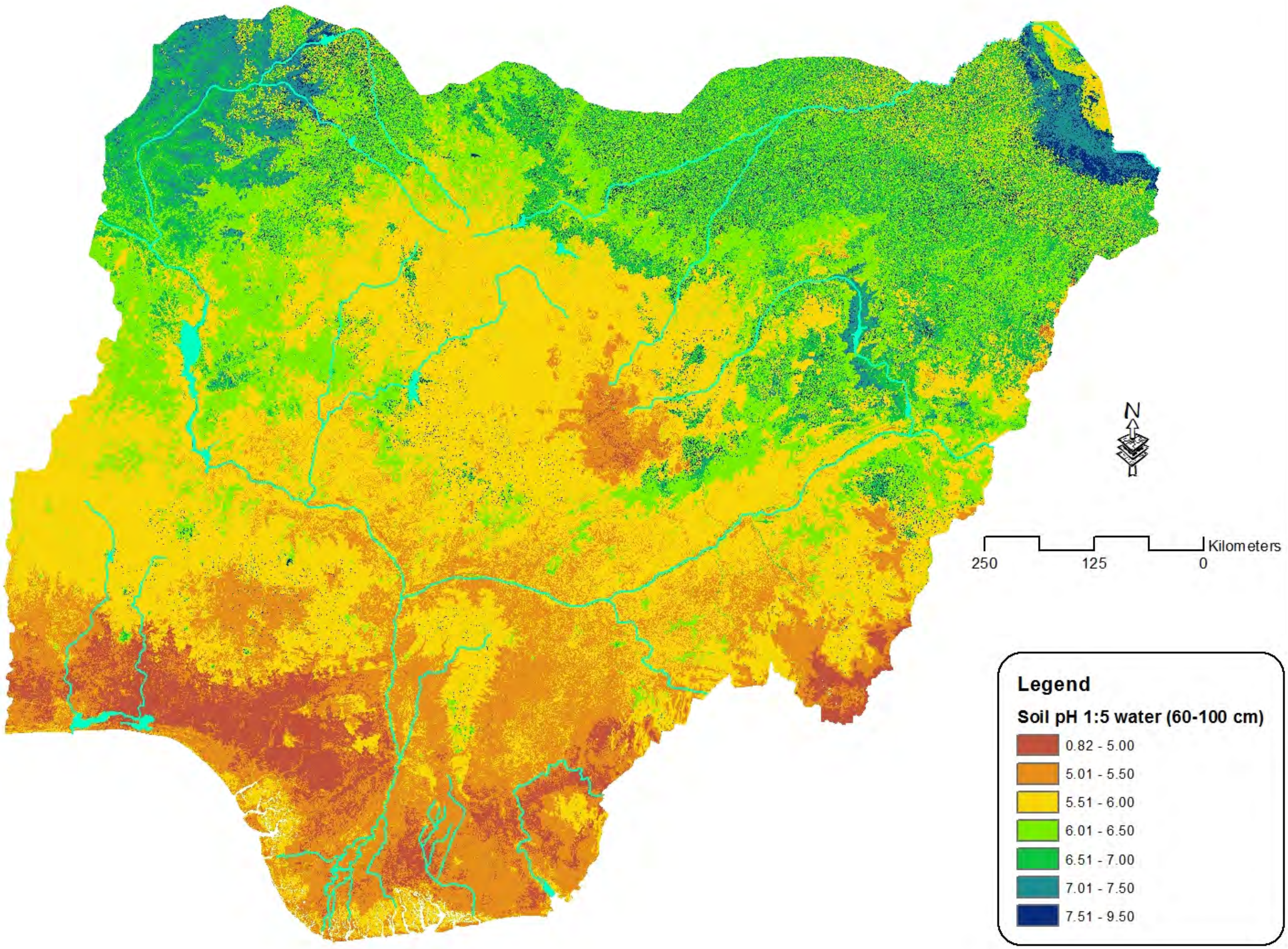
Results for Soil pH in Water

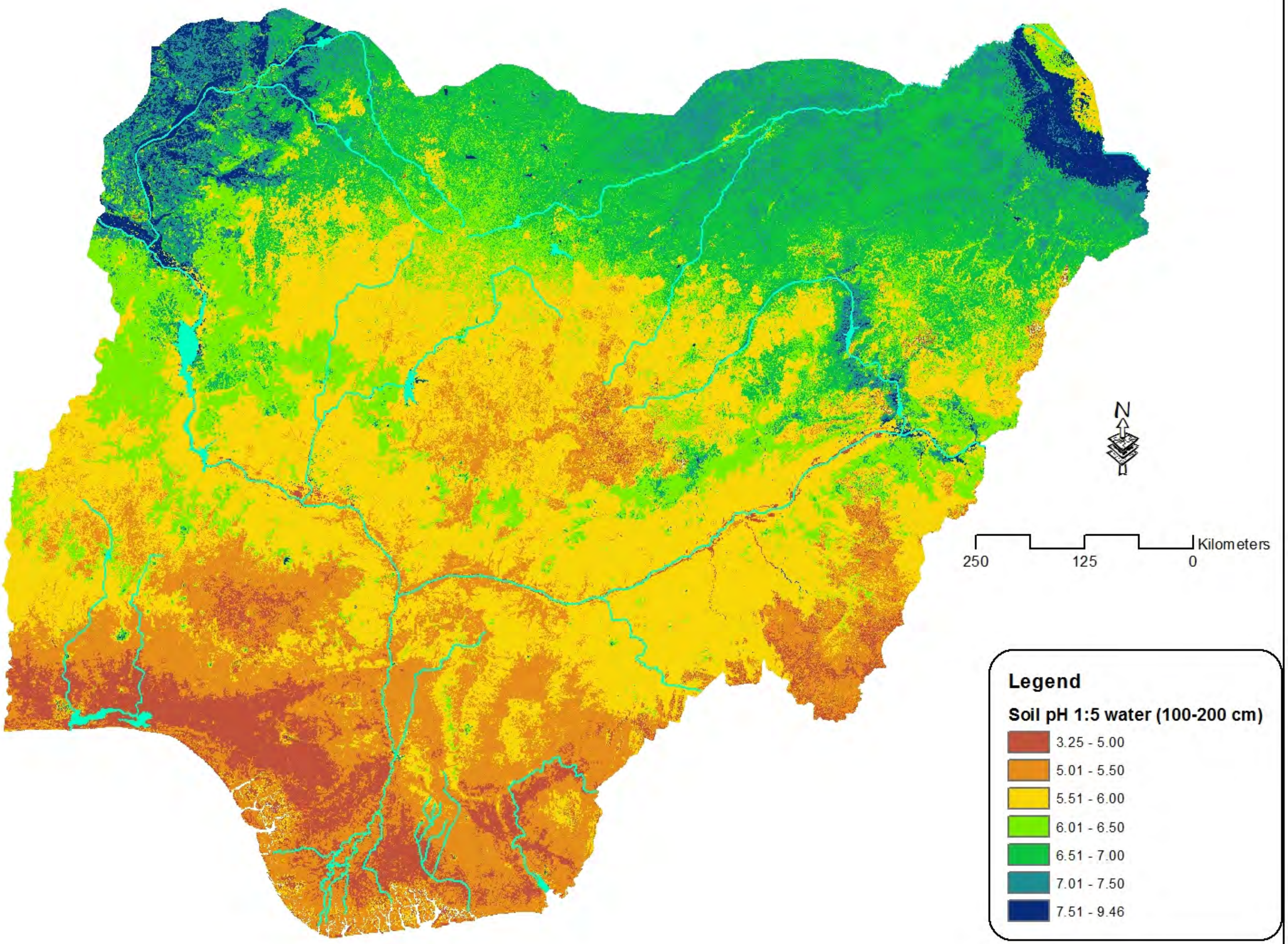

N
250
125
0
Kilometers
Legend
Soil pH 1:5 water (0-5 cm)
3.37 - 5.00
5.01 - 5.50
5.51 - 6.00
6.01 - 6.50
6.51 - 7.00
7.01 - 7.50
7.51 - 9.50


N
250
125
0
Kilometers
Legend
Soil pH 1:5 water (5-15 cm)
3.21 - 5.00
5.01 - 5.50
5.51 - 6.00
6.01 - 6.50
6.51 - 7.00
7.01 - 7.50
7.51 - 9.50


N
250
125
0
Kilometers
Legend
Soil pH 1:5 water (15-30 cm)
3.21 - 5.00
5.01 - 5.50
5.51 - 6.00
6.01 - 6.50
6.51 - 7.00
7.01 - 7.50
7.51 - 9.50


N
250
125
0
Kilometers
Legend
Soil pH 1:5 water (30-60 cm)
3.21 - 5.00
5.01 - 5.50
5.51 - 6.00
6.01 - 6.50
6.51 - 7.00
7.01 - 7.50
7.51 - 9.50


N
250
125
0
Kilometers
Legend
Soil pH 1:5 water (60-100 cm)
0.82 - 5.00
5.01 - 5.50
5.51 - 6.00
6.01 - 6.50
6.51 - 7.00
7.01 - 7.50
7.51 - 9.50


N
250
125
0
Kilometers
Legend
Soil pH 1:5 water (100-200 cm)
3.25 - 5.00
5.01 - 5.50
5.51 - 6.00
6.01 - 6.50
6.51 - 7.00
7.01 - 7.50
7.51 - 9.46

Validation of output maps

- Used ten-fold cross-validation trials in which prediction accuracy of 10% of the samples are tested using 90% of the samples
- The accuracy were determined by
  - root mean square error- an indication of average error or accuracy,
  - relative error- the ratio of average error to the error that would result from always predicting the mean value and should be less than 1,
  - concordance correlation coefficient which determines the agreement between measured and predicted values

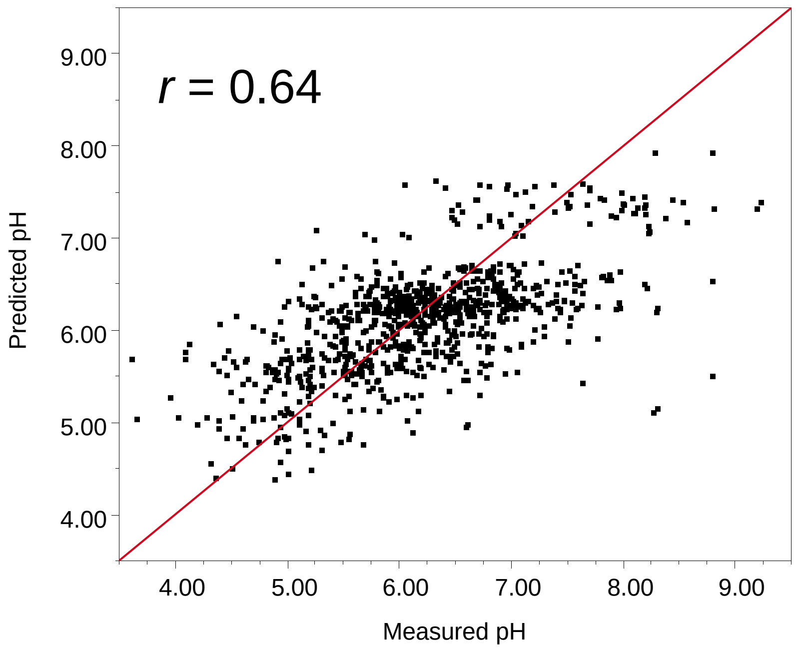
Validation of output maps

Soil pH			
Depth (cm)	Average error (pH unit)	†Relative error	Correlation Coefficient
0-5	0.59	0.85	0.64
5-15	0.55	0.80	0.61
15-30	0.52	0.73	0.67
30-60	0.55	0.70	0.68
60-100	0.56	0.63	0.72
100-200	0.59	0.58	0.76
Soil organic carbon			
Depth	Average error (g/kg)	Relative error	Correlation Coefficient
0-5	4.93	0.73	0.60
5-15	4.48	0.89	0.49
15-30	2.66	0.80	0.60
30-60	2.67	0.80	0.60
60-100	1.52	0.91	0.54
100-200	1.00	0.77	0.62

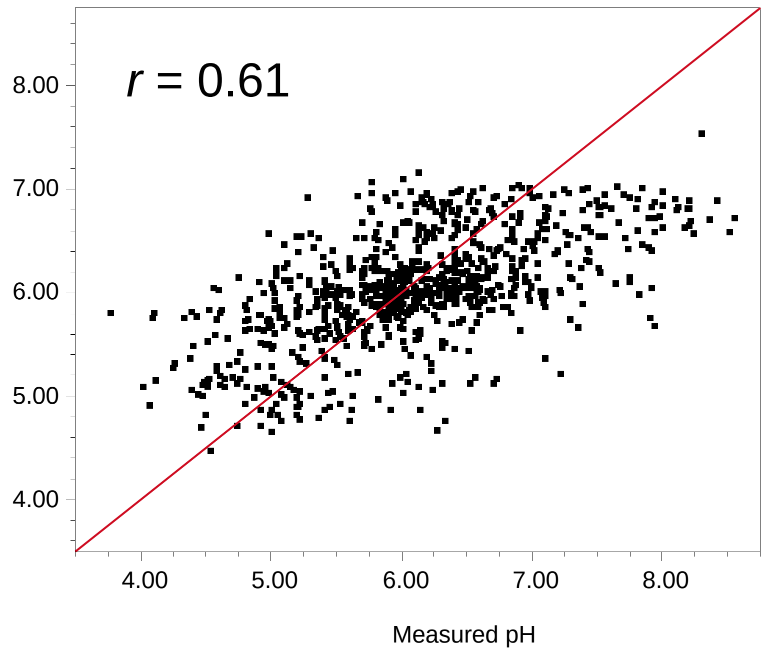
†Relative error is the ratio of average error and the error that would result from always predicting the mean value and should be less than 1

Validation of output maps

pH (0-5 cm depth)



pH (5-15 cm depth)



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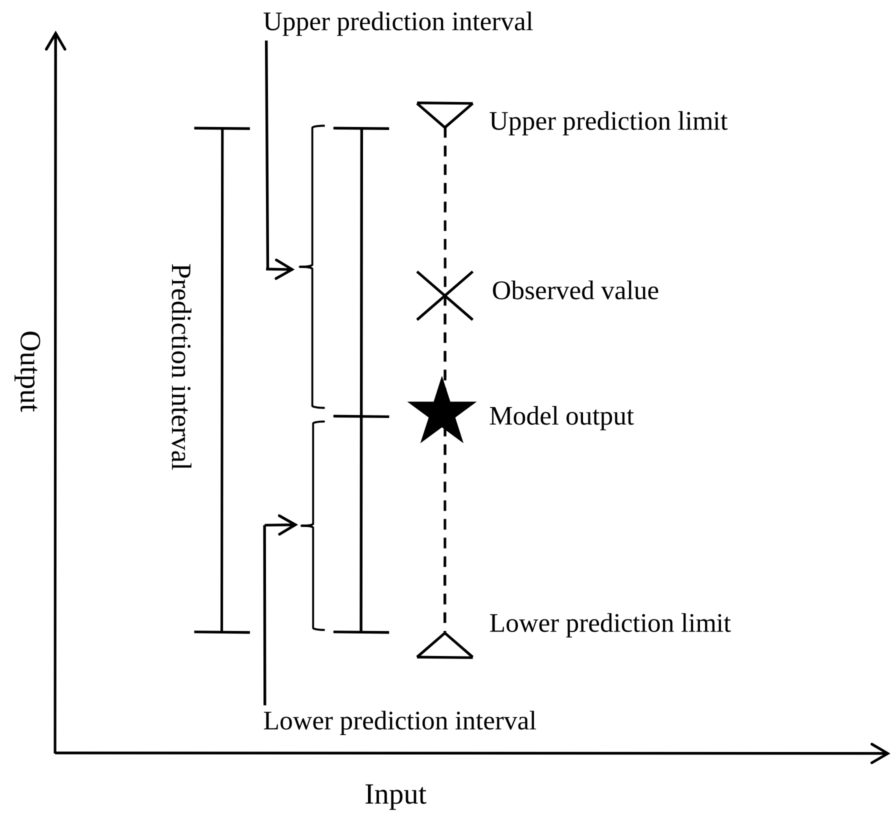
What next

- Work is ongoing for particle-size fractions, CEC and others
- Perform more detailed uncertainty analysis

Uncertainty Estimation

Use Malone et al (2011) Prediction Interval Approach

Derive **upper and lower prediction limits (PREDICTION INTERVAL)** based on the model errors and clustering for every pixel/node across spatial domain to a depth of 2m.



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- Tom Bishop
- Brendan Malone
- ISRIC
- And Others

ISRIC World Soil Information

Thank you for listening