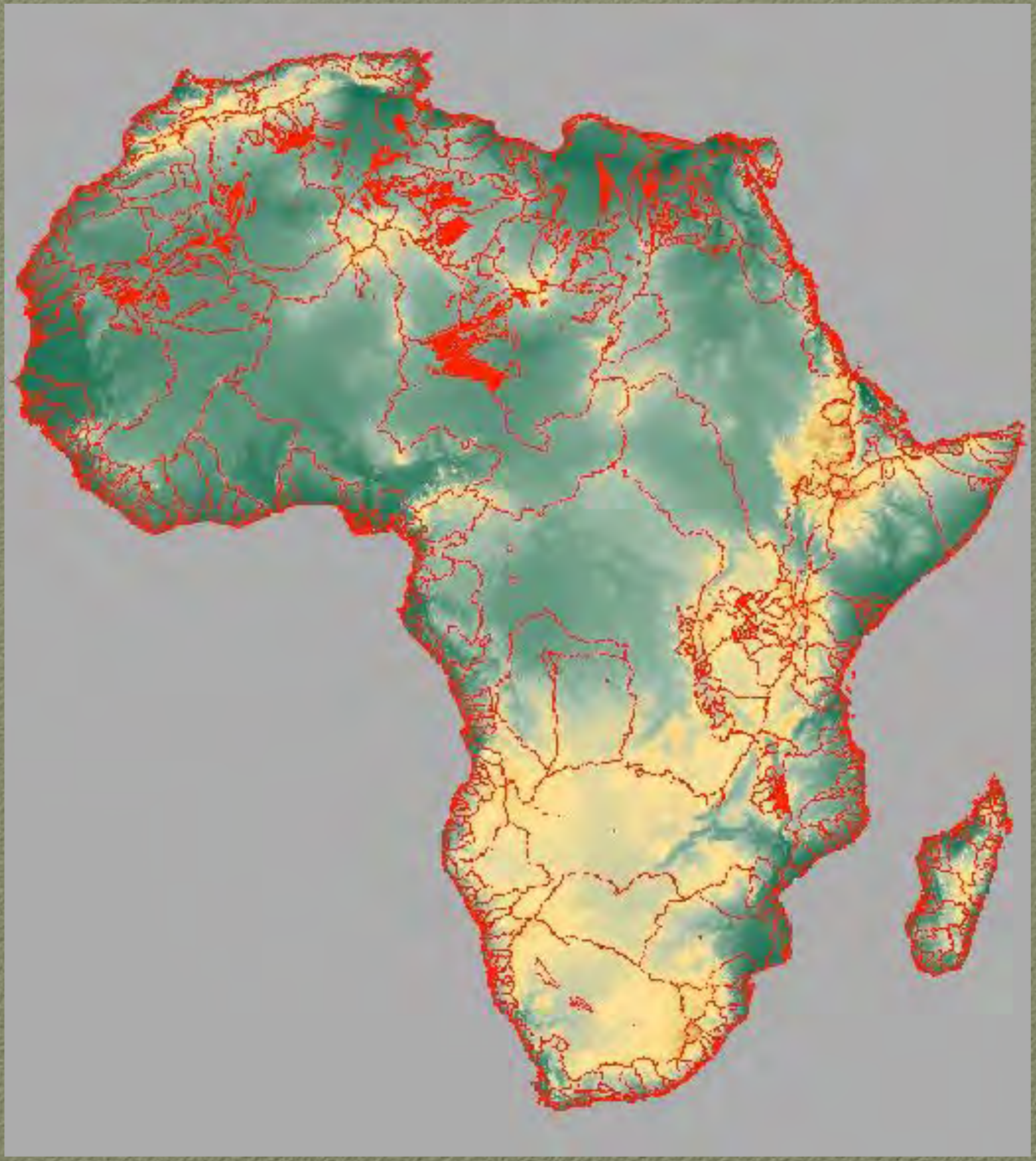
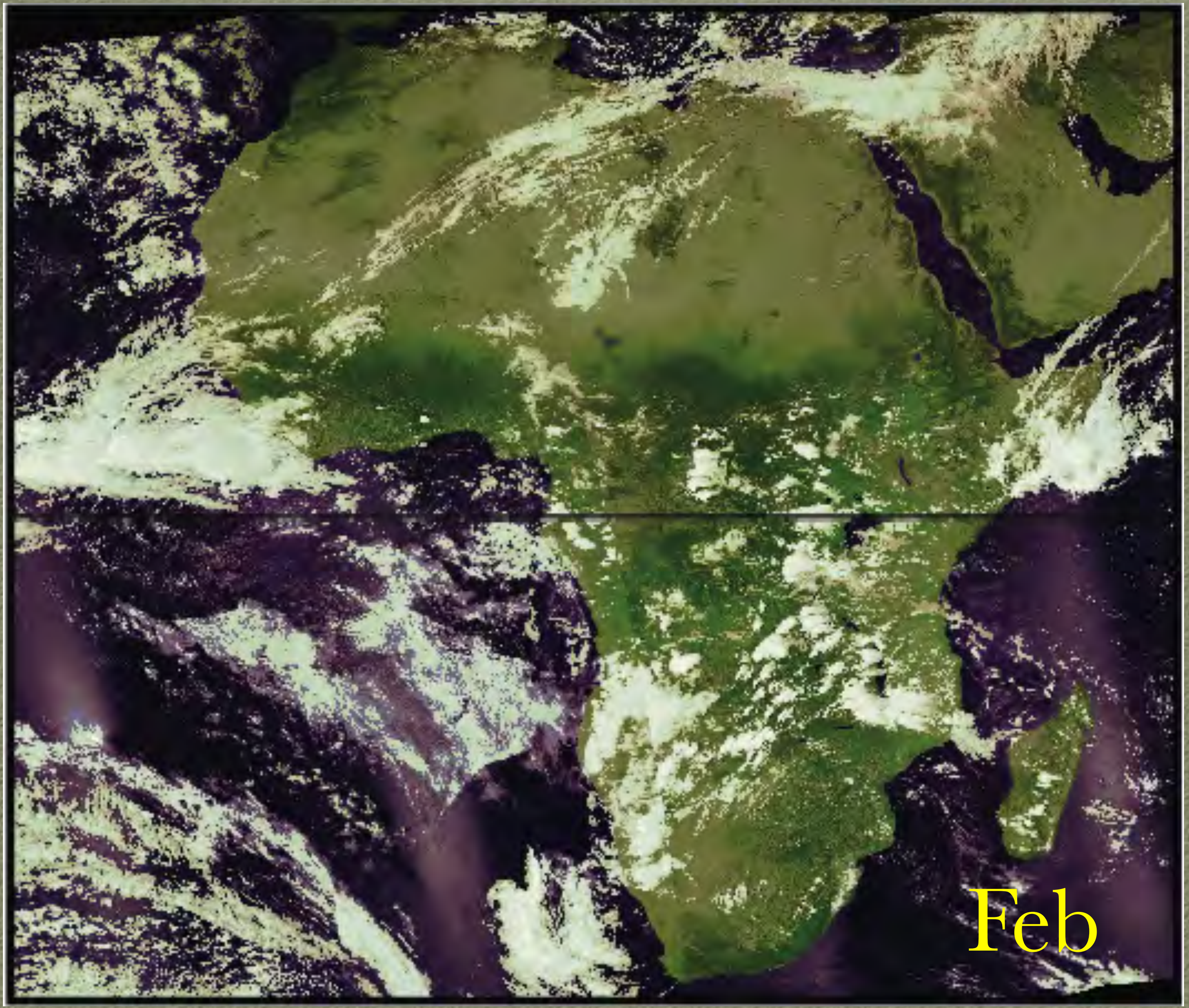
PART 1 - Data



Weather satellite data
Available for each 15
minutes

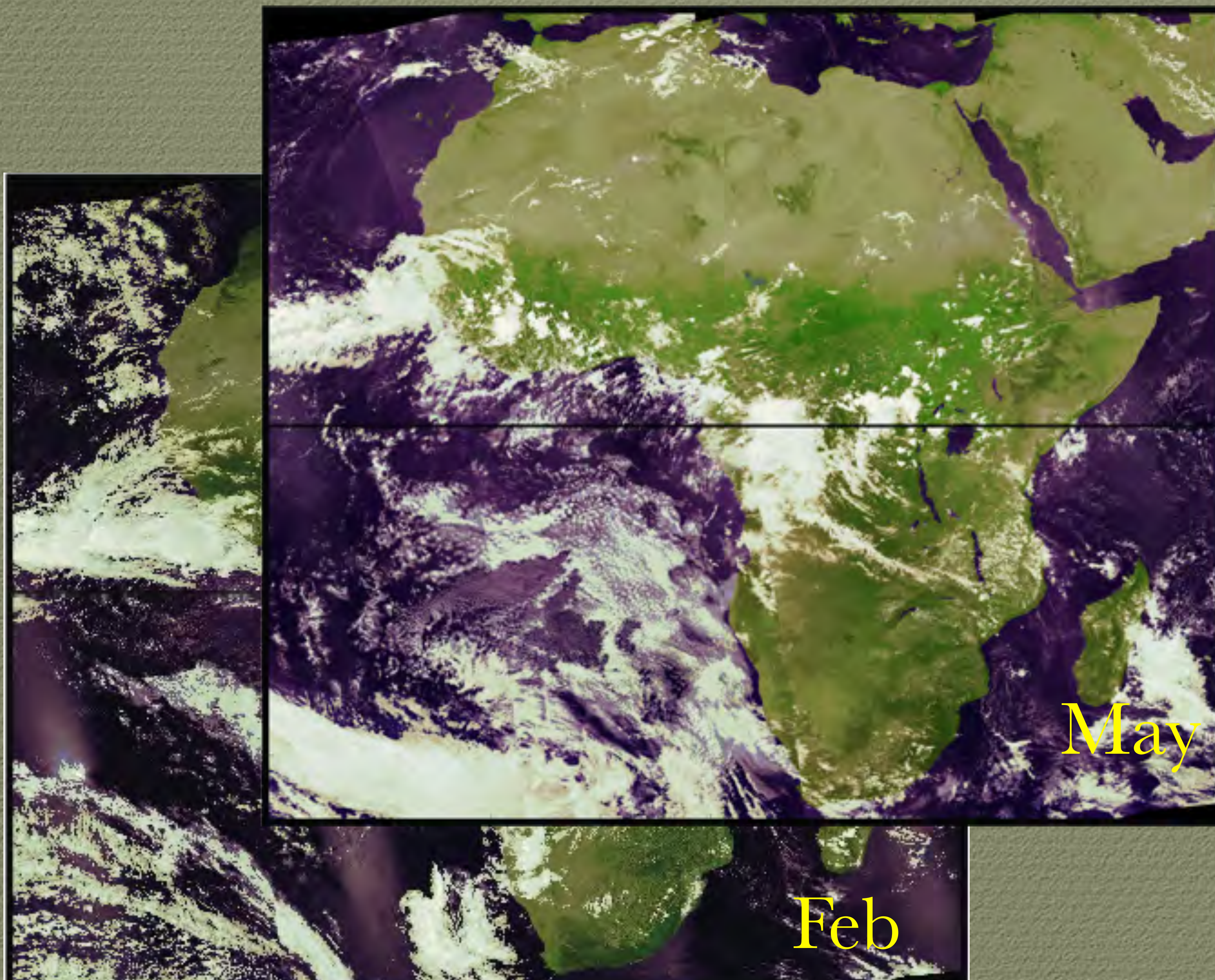
Illustrated with
NOAA-AVHRR
available since 1981
online resource

Weather satellite data
Available for each 15 minutes



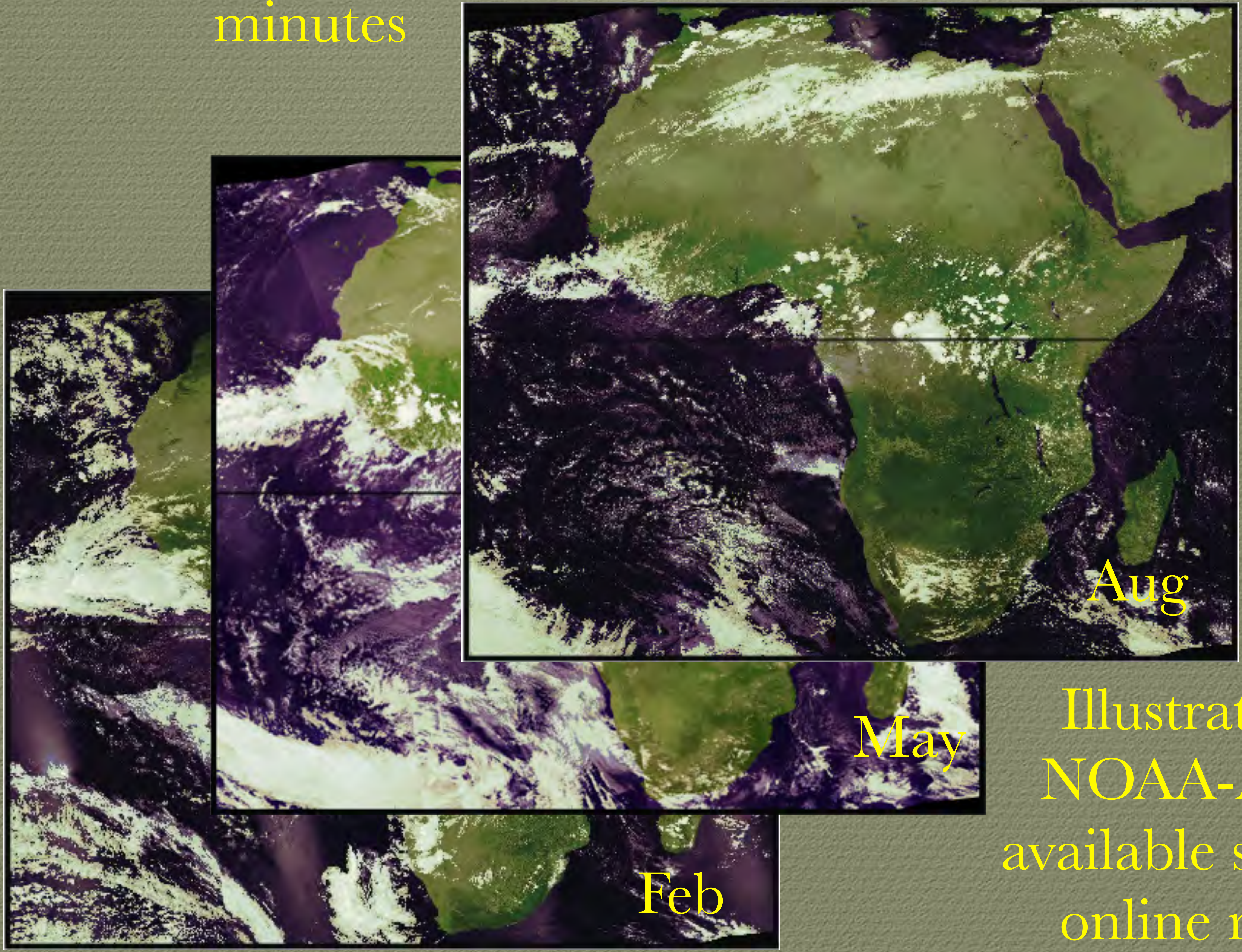
Illustrated with NOAA-AVHRR available since 1981 online resource

Weather satellite data
Available for each 15 minutes



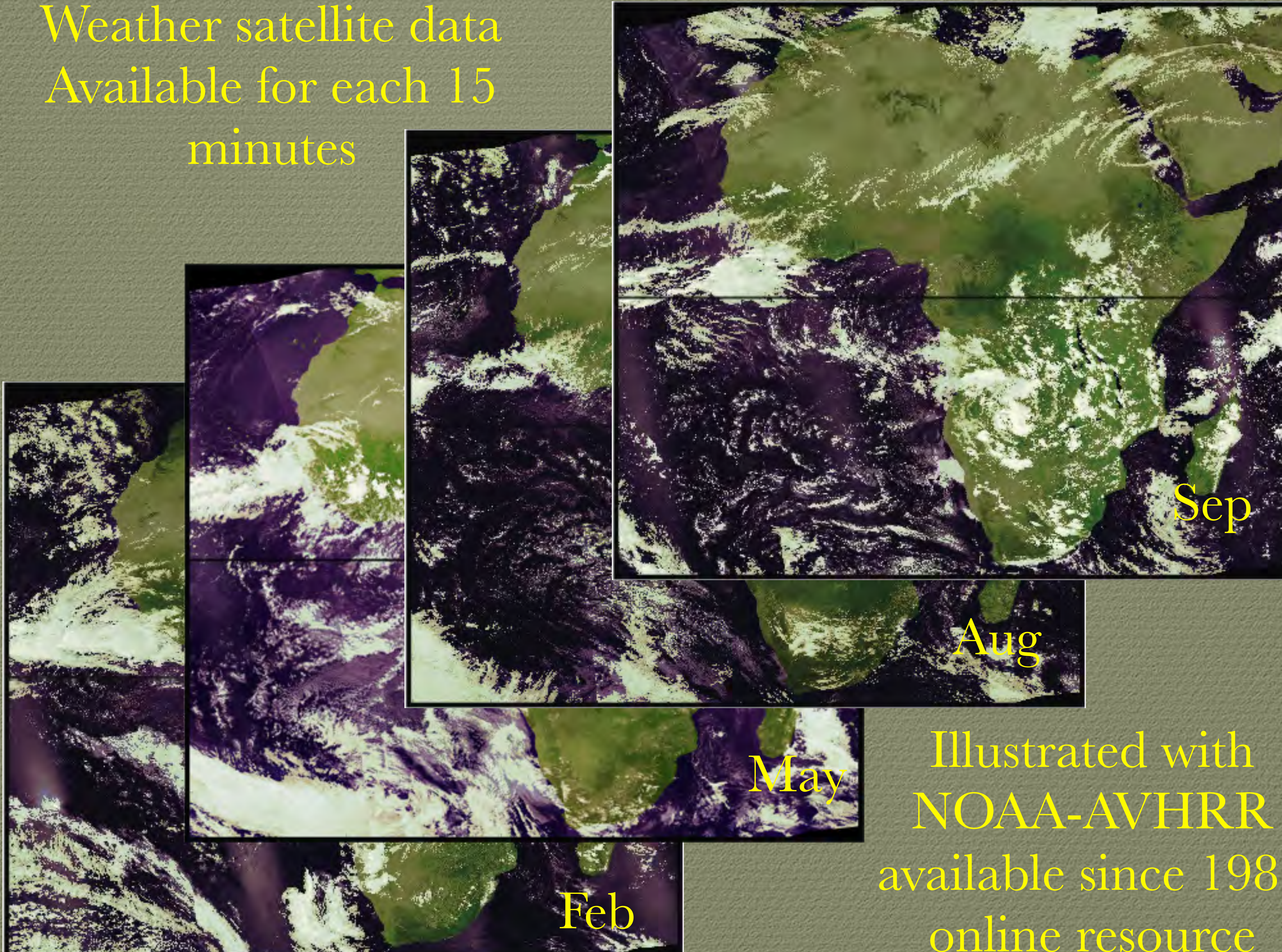
Illustrated with NOAA-AVHRR available since 1981 online resource

Weather satellite data Available for each 15 minutes



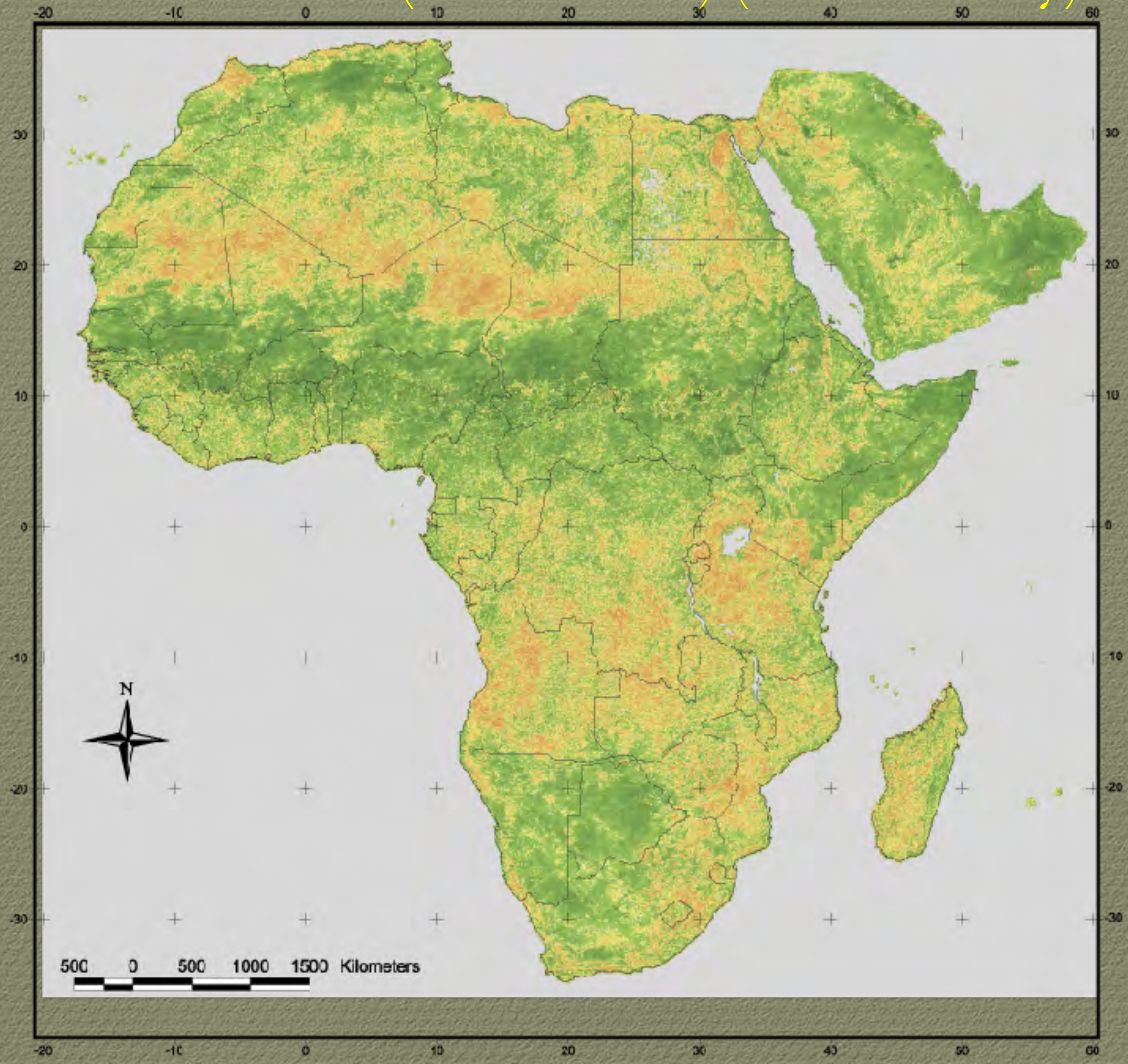
Illustrated with NOAA-AVHRR available since 1981 online resource

Weather satellite data Available for each 15 minutes



Illustrated with NOAA-AVHRR available since 1981 online resource

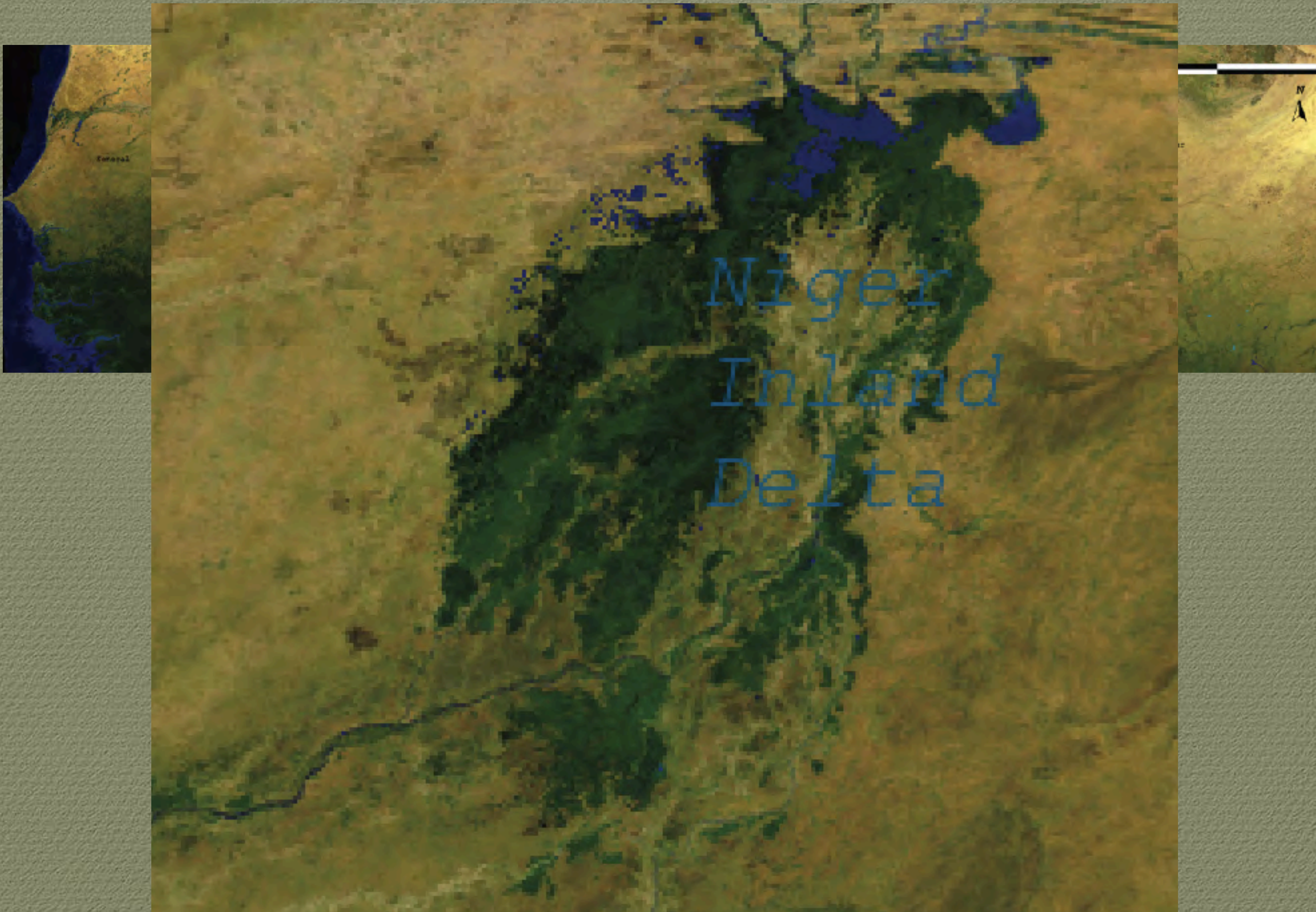
Vegetation change derived from weather satellite data (1981-2009) (each 10 day)



MODIS data

We have weekly MODIS data on vegetation and reflectance for the last 10 years. About 10000 Scenes.

MODIS data



The Landsat program

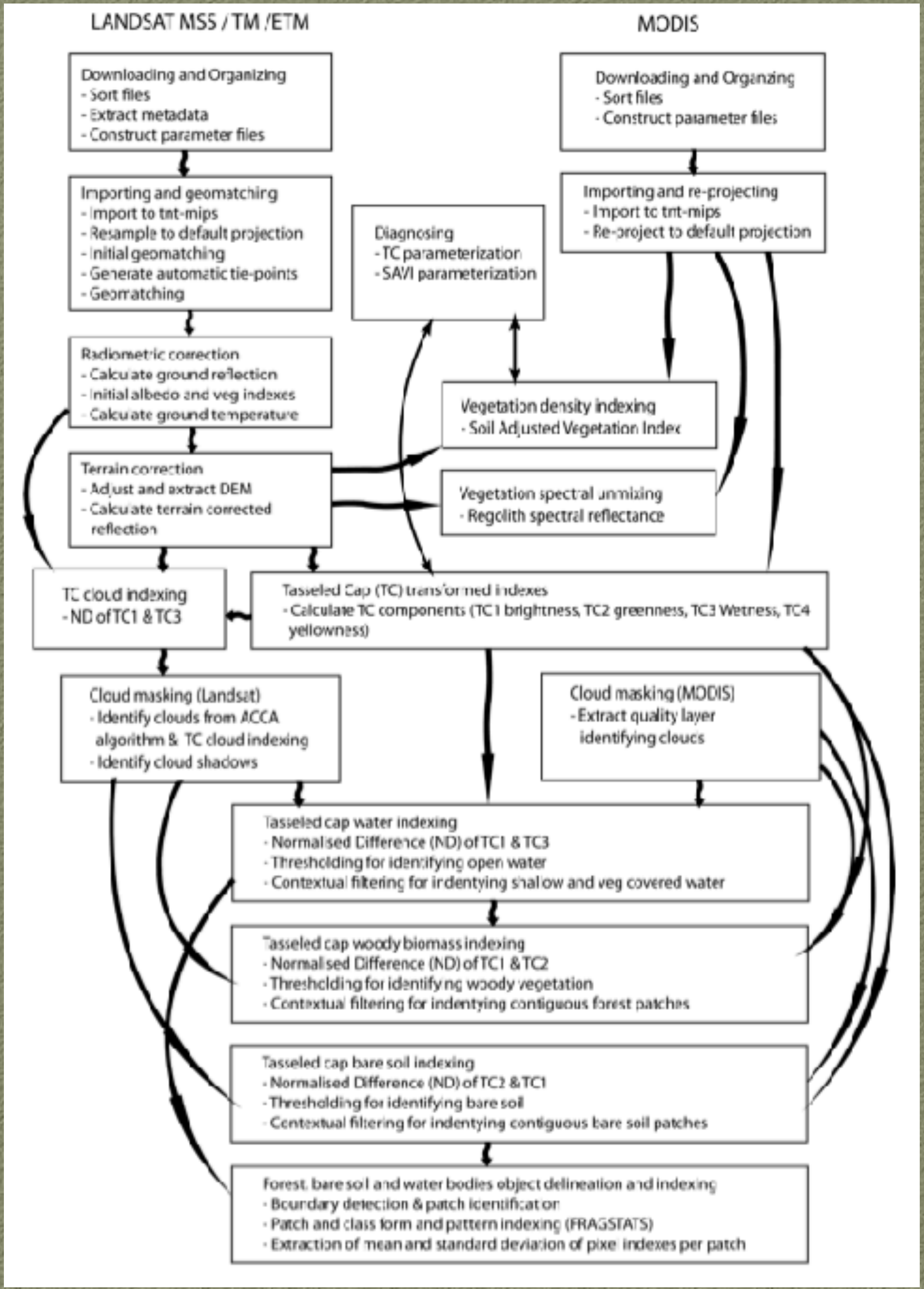
We have about 10 000 Landsat scenes, from all the sensors:

MSS 1
MSS 2
MSS 3
MSS 4
MSS 5
TM 4
TM 5
ETM 7

Other satellite data sources

We also process data from
ASTER
Rapid Eye
Quickbird
TOMS
SeaWifs
and more sensors

PART 2 - Processing



Downloading and organizing

Download from FTP servers, organizing into folders and register to database is automated by using scripting (Tcl-Expect, applescript and shell commands). Servers not allowing FTP but delivering data upon request must be visited manually at present.

Importing and projecting

Satellite images come in an incredible number of different formats and projections. And not seldom is the geo-registering a bit out of place. This step can not be fully automated. The most tedious part of identifying ground control points (points with an exactly known position) is, however automated. But the correctness of the geo-registering must still be manually checked.

Reflectance correction

Of the satellites we use, only the data from MODIS is delivered as ground reflectance data. For other sensors we need to convert the data from the registered electromagnetic signal at the sensor to ground reflectance. This demands detailed knowledge about the sensor calibration, the distance to the sun, the suns elevation at the time of image acquisition, and the transparency of the atmosphere at the time of acquisition.

Terrain correction

For high resolution imagery it is essential to correct for terrain shading and shadows. For medium to low resolution data it is not that important. This demands a detail Digital Elevation Model (DEM). For this we use the Shuttle Radar Topography Mission (SRTM) or the ASTER DEM. The former is better over flatter areas, whereas the latter is better in very steep terrain (e.g. Tibet).

Spectral classification

The automated processing chain includes the option of automated Spectral Angle Mapping (SAM) of any feature in the scene. By default water, forests, grasslands and some other features are classified by using global spectral libraries. The spectral data is extracted to fit the individual sensors used in the processing chain. This data is used to support some of the subsequent processing, and can also be used for feature extraction.

Band transformation

The satellite sensors register electromagnetic radiation in different wavelength bands. The data can not be directly compared To overcome this we use a pre-determined Principal Component Analysis methods called Tasseled Cap. It was first defined for Landsat data, but is now also defined for e.g. MODIS, ASTER and Quickbird. By applying this transformation we derive 4 physically related indexes (brightness, greenness, wetness and yellowness) that are comparable. These 4 indexes are then used in most of the subsequent processing, which is thus the same for data derived from all sensors.

Cloud indexing and masking

Identifying clouds and cloud shadows is crucial for getting the correct information from the satellite images. The hitherto published cloud identification methods did not meet the standard we needed. We have hence developed a set of different cloud detection routines. This turned out to be the most difficult task in the development of the automated processing chain.

Water indexing and masking

Water is not trivial to detect accurately in satellite imagery. But without an accurate water mask the detection of forests, clouds and cloud shadows becomes biased. The surface wetness is also in itself an important indicator. Adopting time series analysis it can for instance be used for predicting soil water conditions and forecast crop and vegetation production. Again we were forced to develop our own water indexing and masking algorithms to get the quality we desired.

Woody biomass indexing and forest masking

Woody biomass reflect electromagnetic radiation differently compared to non-woody vegetation. We used this well known difference to design an index for woody biomass, which we then threshold to automatically derive forests from the satellite images. Preliminary results indicate that this index is well correlated with stem density on the ground.

Bare soil and organic matter indexing

Areas without photosynthetic pigments are automatically extracted (excluding clouds and water). These Non Photosynthetic areas are then indexed and divided into area with and without organic residue.

Pixel unmixing

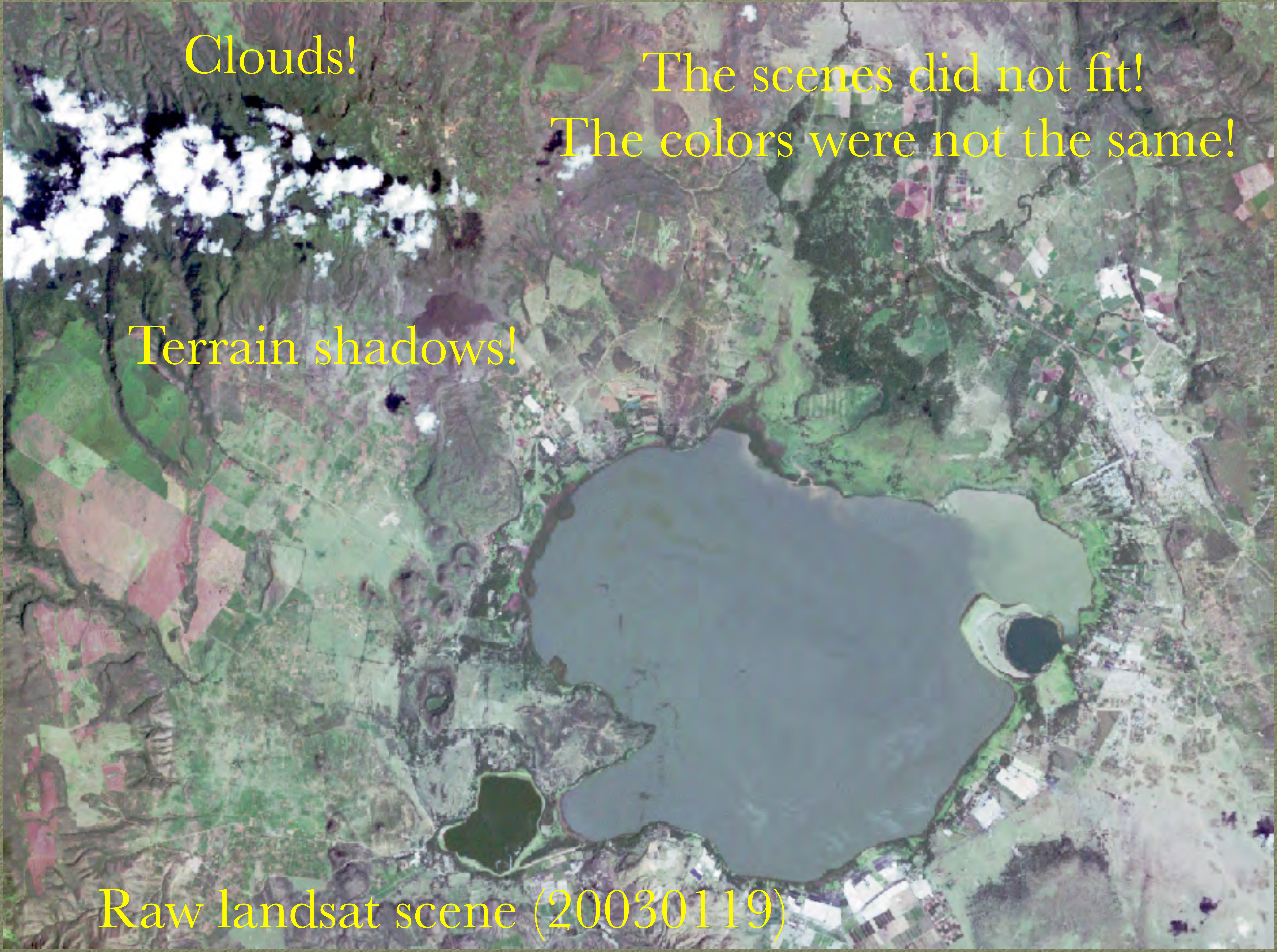
The processing chain includes an automatic forward (or data) driven pixel unmixing. As we do not have information on the spectral end-members for each scene we adopt a method identifying the spectral signal from one material (e.g. vegetation) based on an index (e.g. vegetation index). We then use the index value in each pixel to extract the part of the reflectance in that pixel that is derived from the identified material, and hypothetically we can then unmix the reflectance from the material and other stuff.

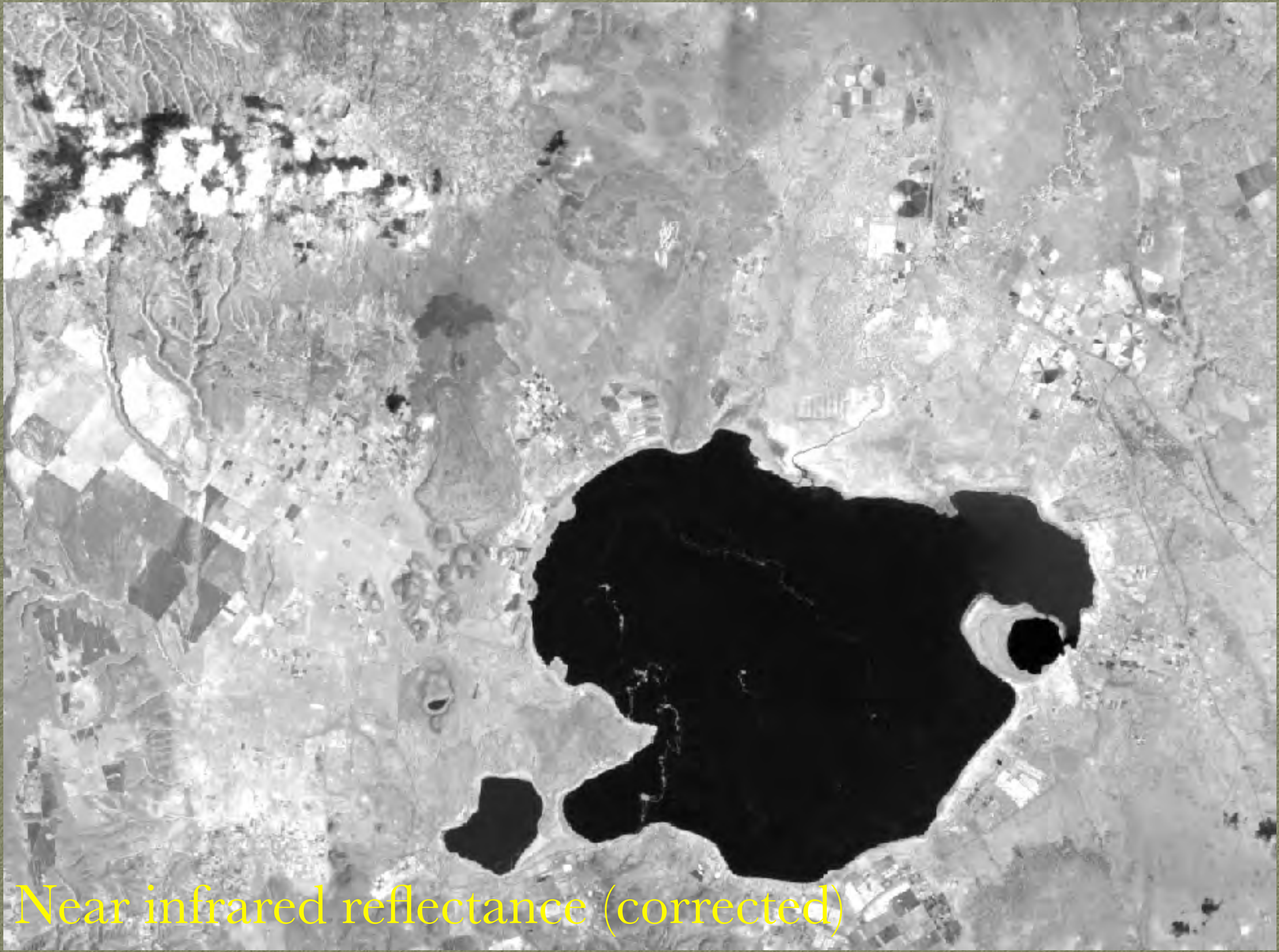
Feature structural indexing

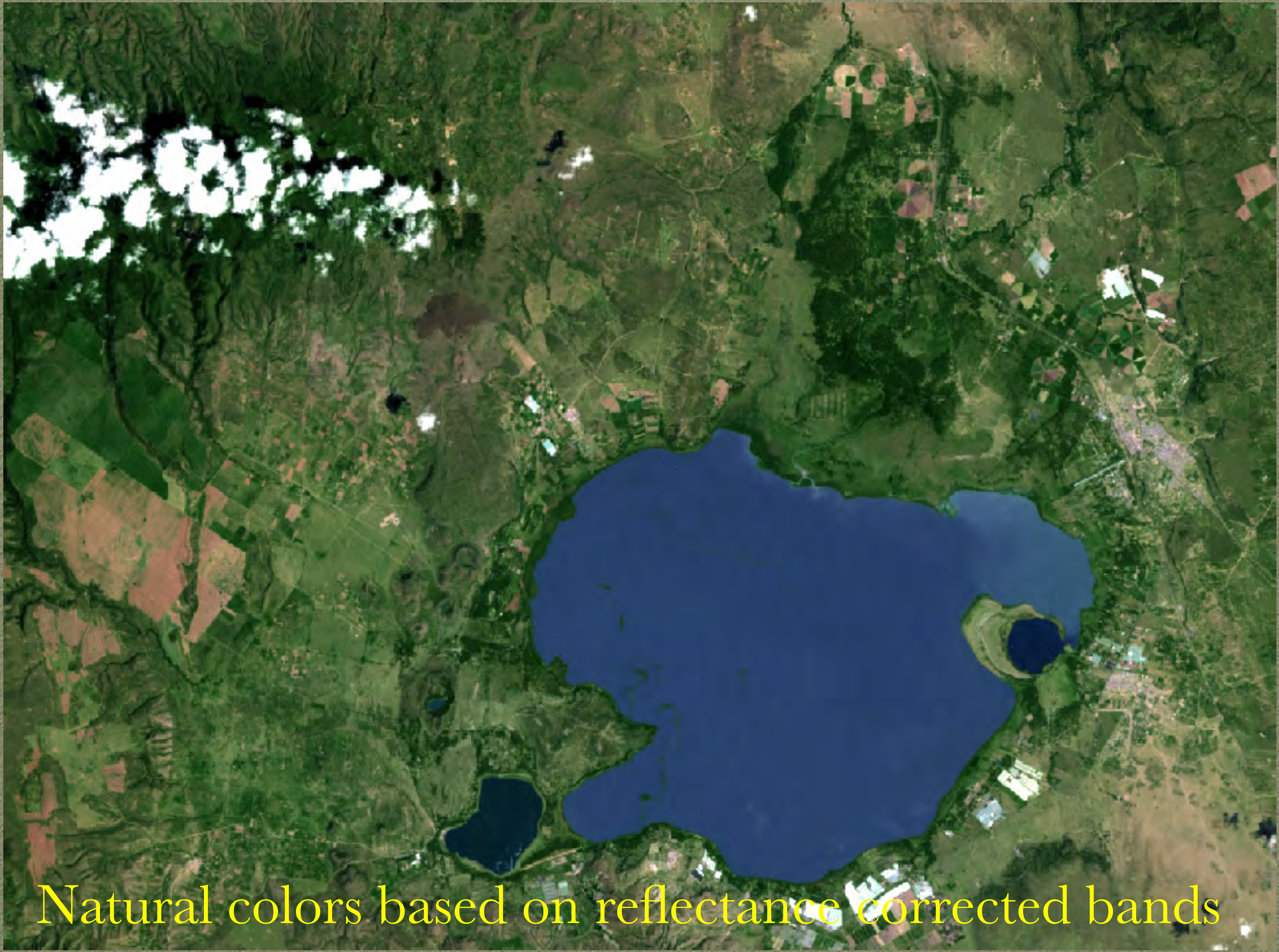
If the processing chain is set to produce feature classes as outcomes, we can use the features as objects and calculate patch, class and regional indexes. Patch indexes describe the structure of a single feature (size, perimeter, core area, edge contrast etc). Class indexes describe the features of the same class within a defined region (total number of features, total area, relative area, density etc). Region indexes describe the matrix of the entire landscape under study.

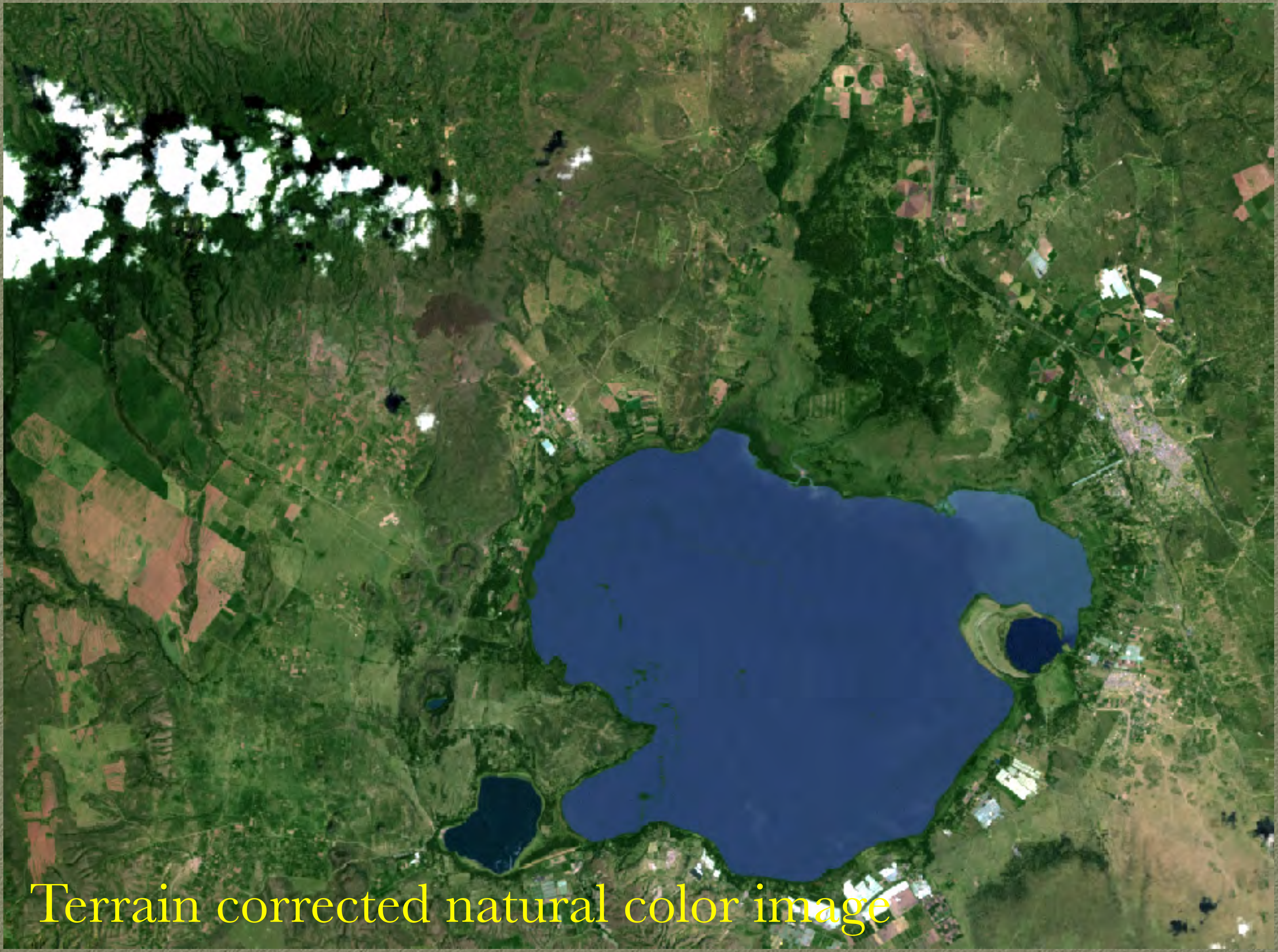
PART 3 - Processing example

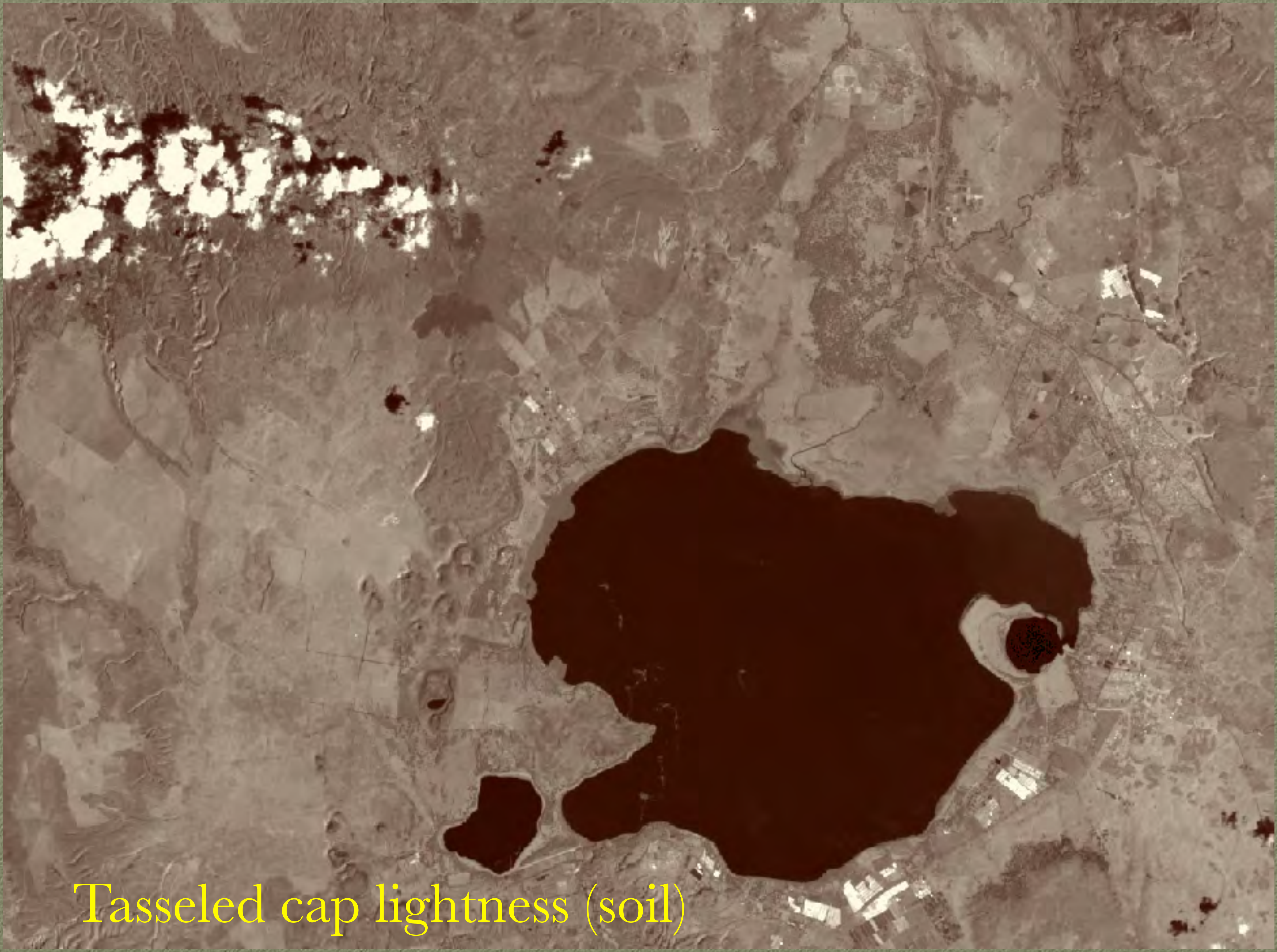

Raw landsat scene (19950121)

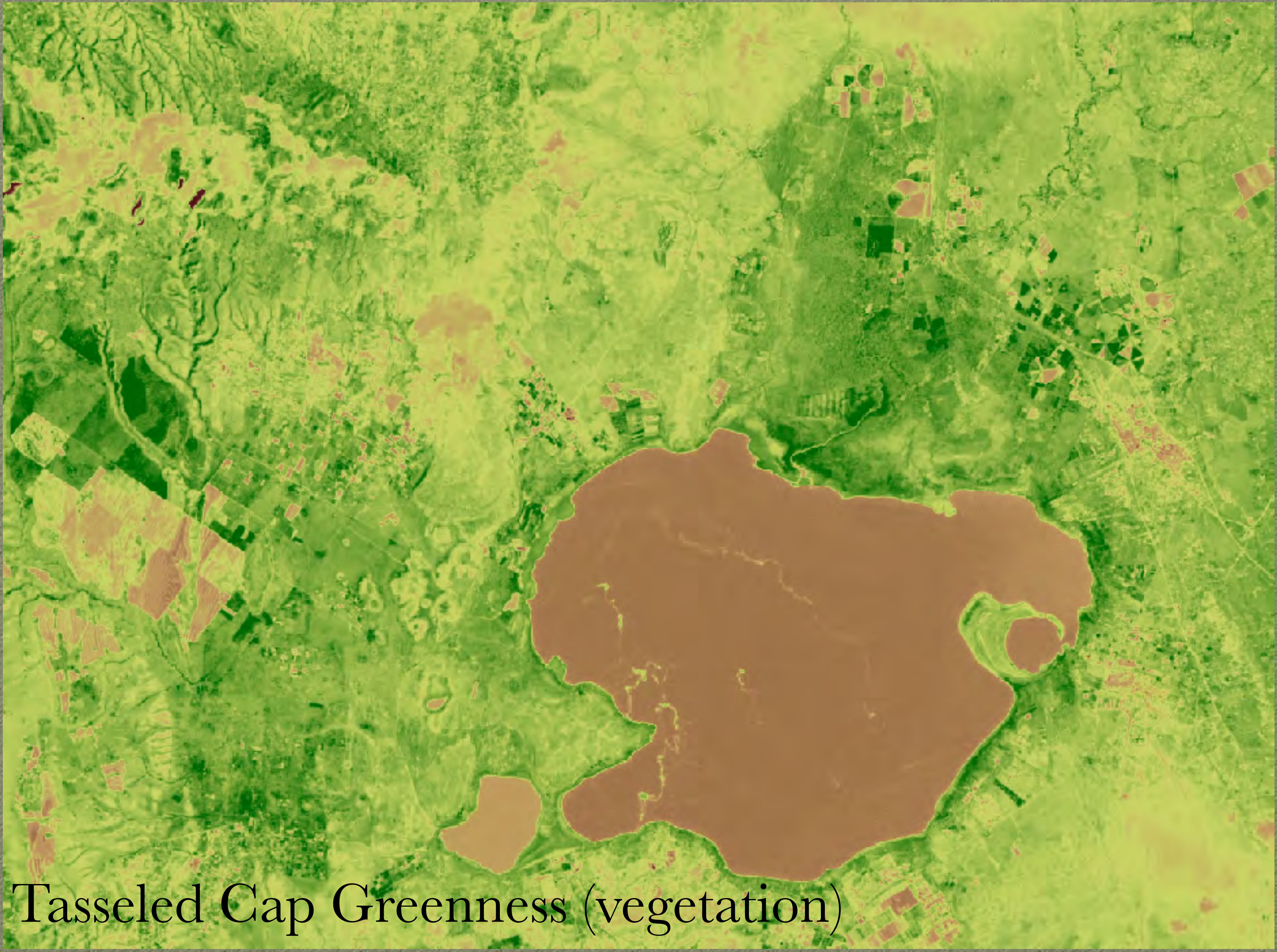

Clouds!
The scenes did not fit!
The colors were not the same!
Terrain shadows!
Raw landsat scene (20030119)


Near infrared reflectance (corrected)

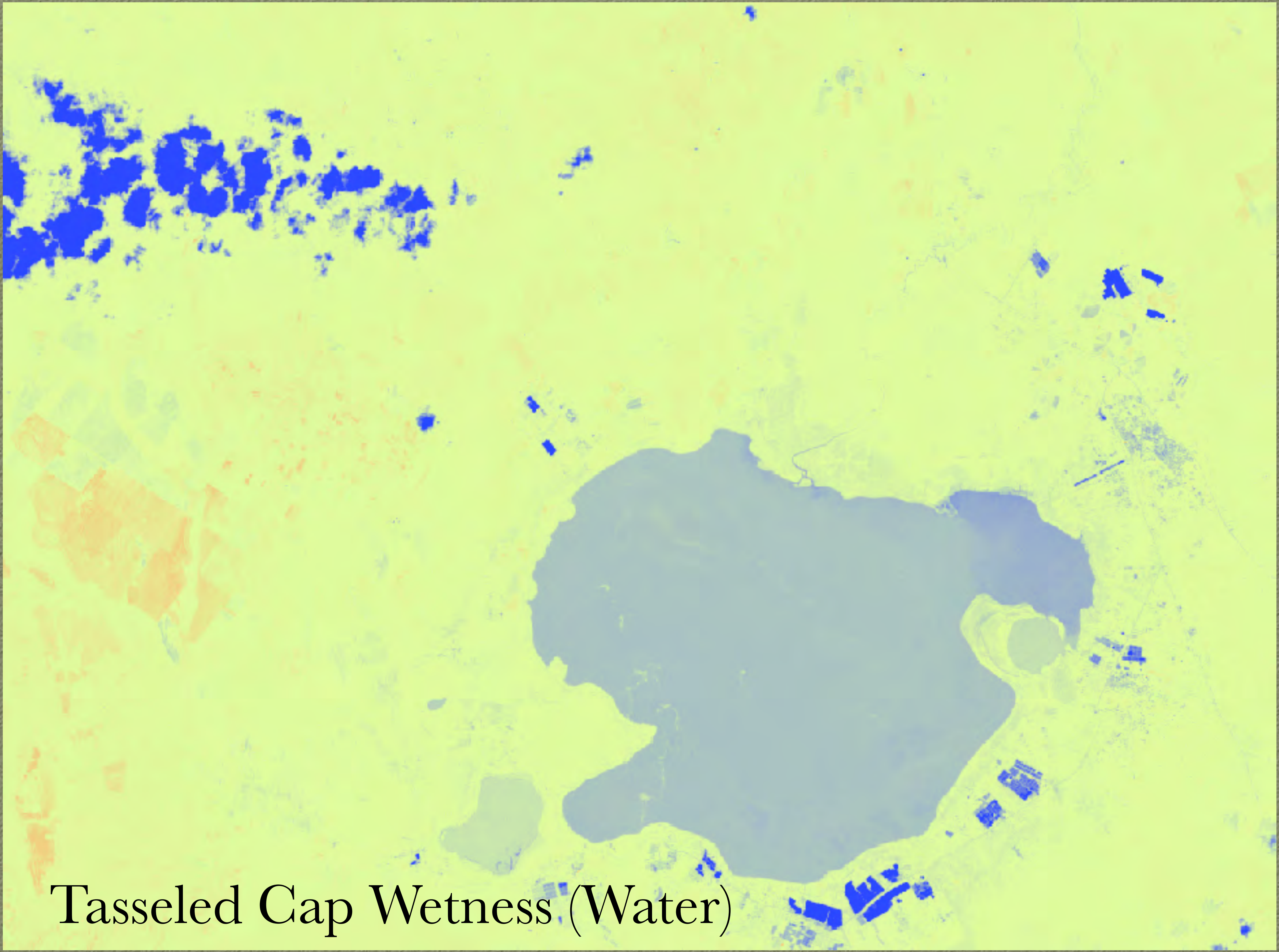

Natural colors based on reflectance corrected bands

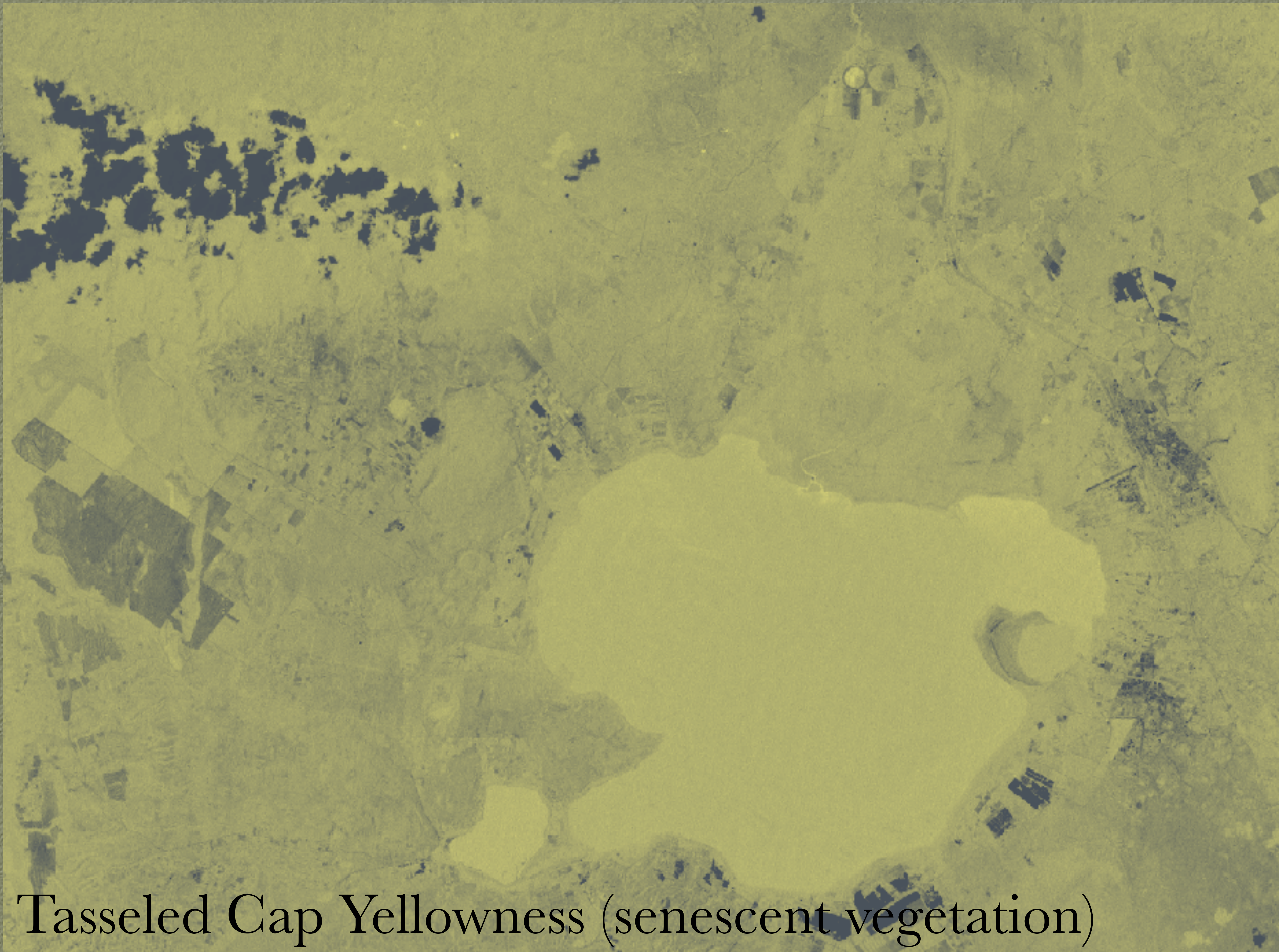

Terrain corrected natural color image


Tasseled cap lightness (soil)

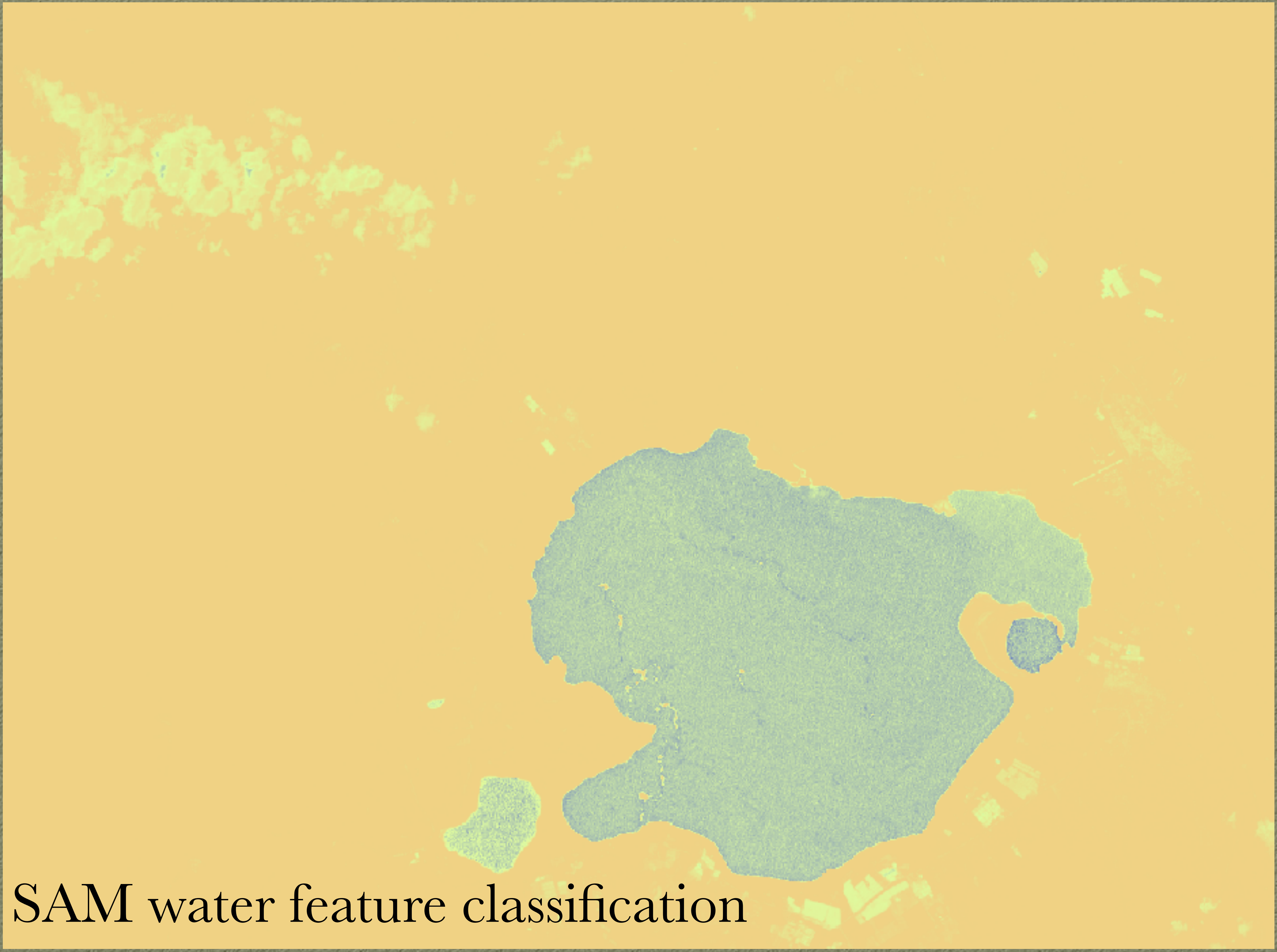


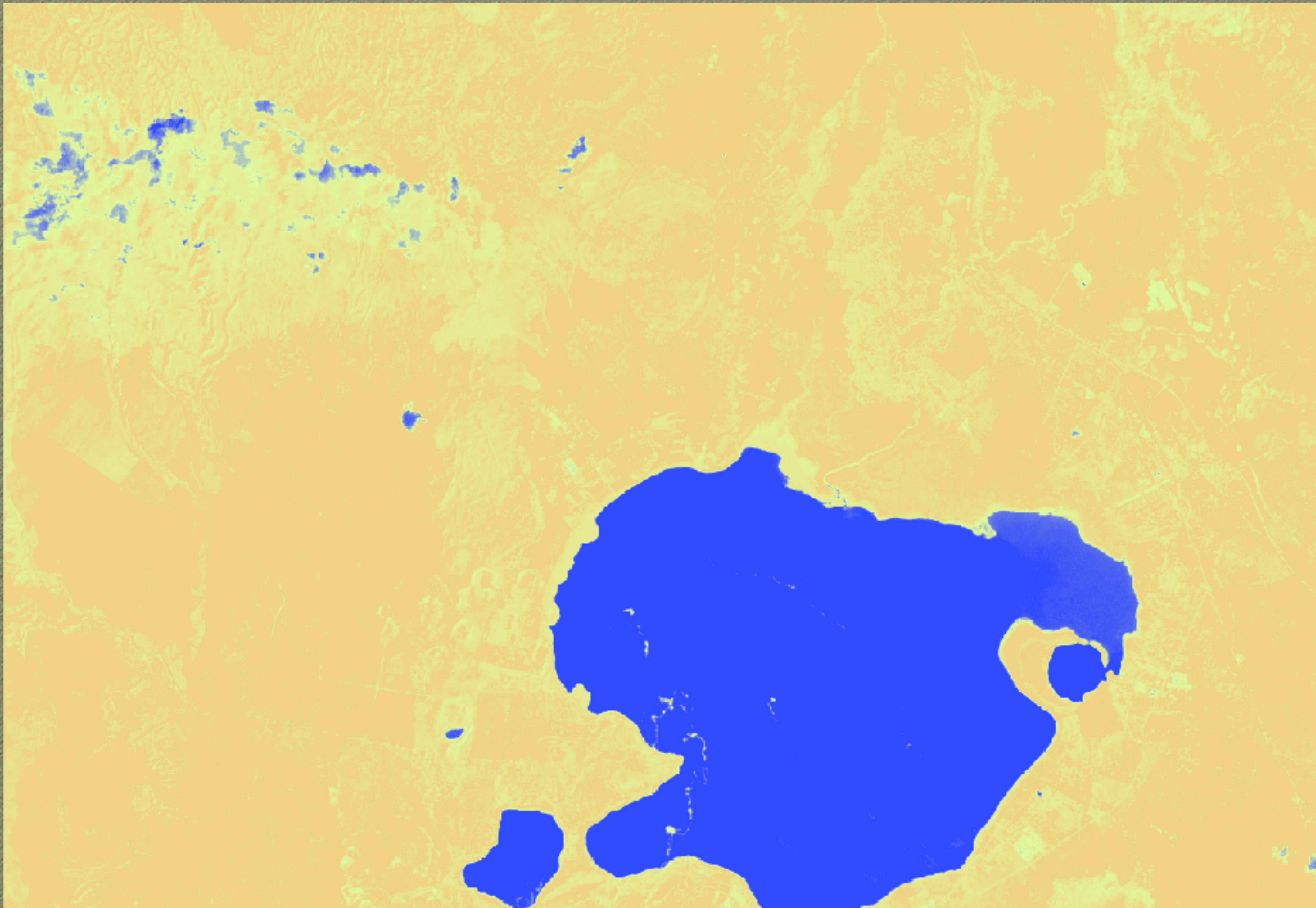
Tasseled Cap Greenness (vegetation)


Tasseled Cap Wetness (Water)

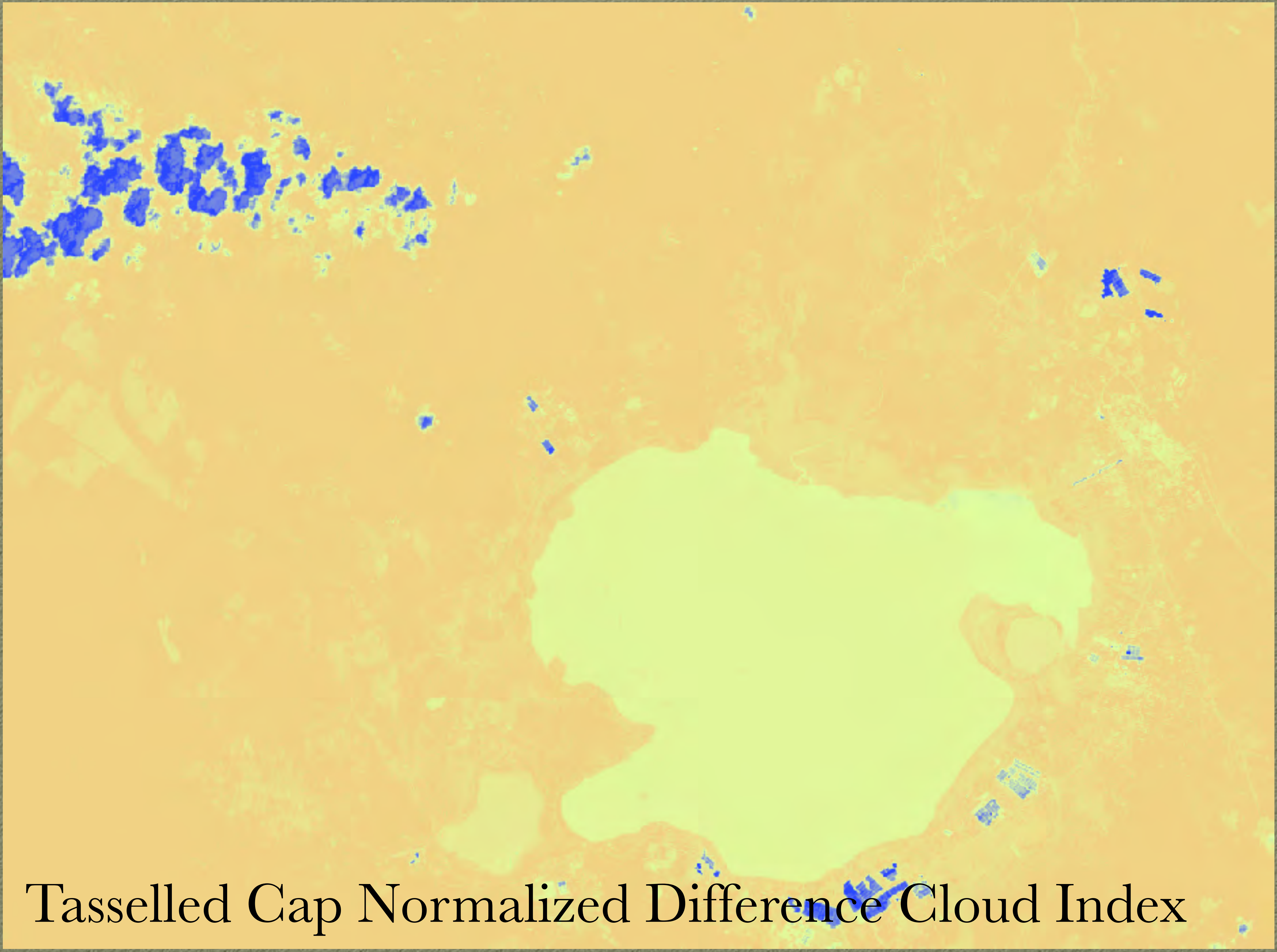


Tasseled Cap Yellowness (senescent vegetation)

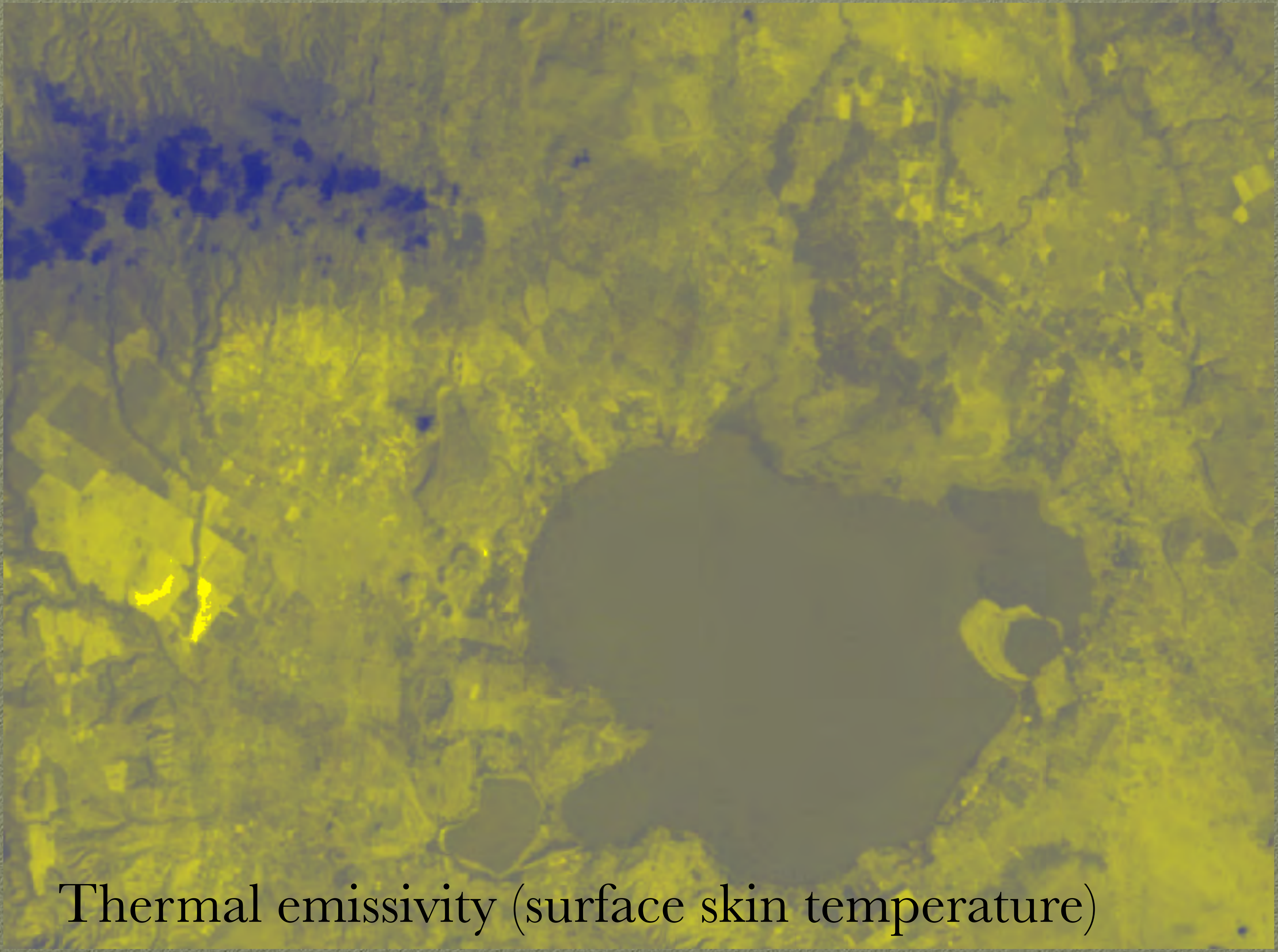

SAM water feature classification

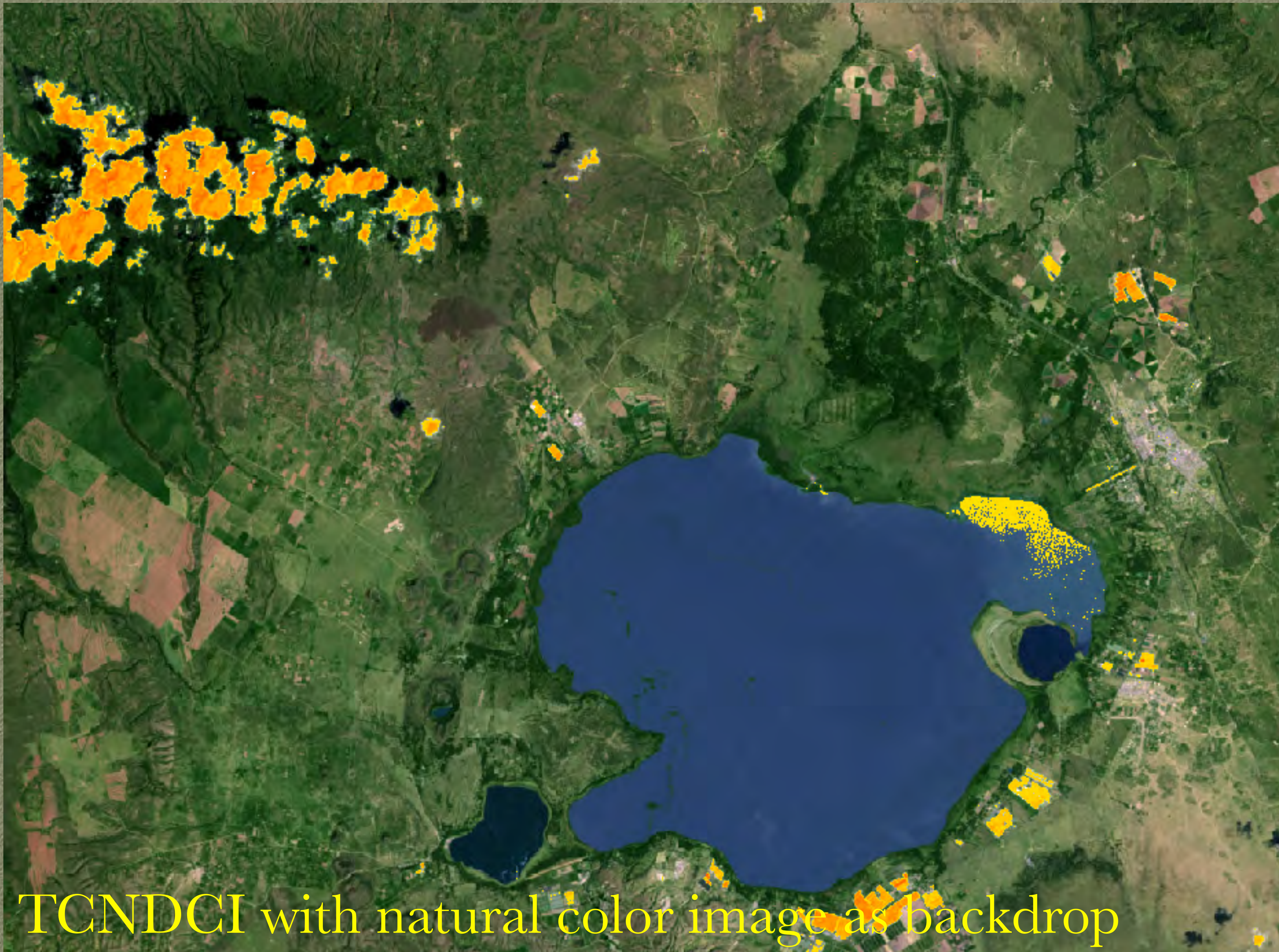


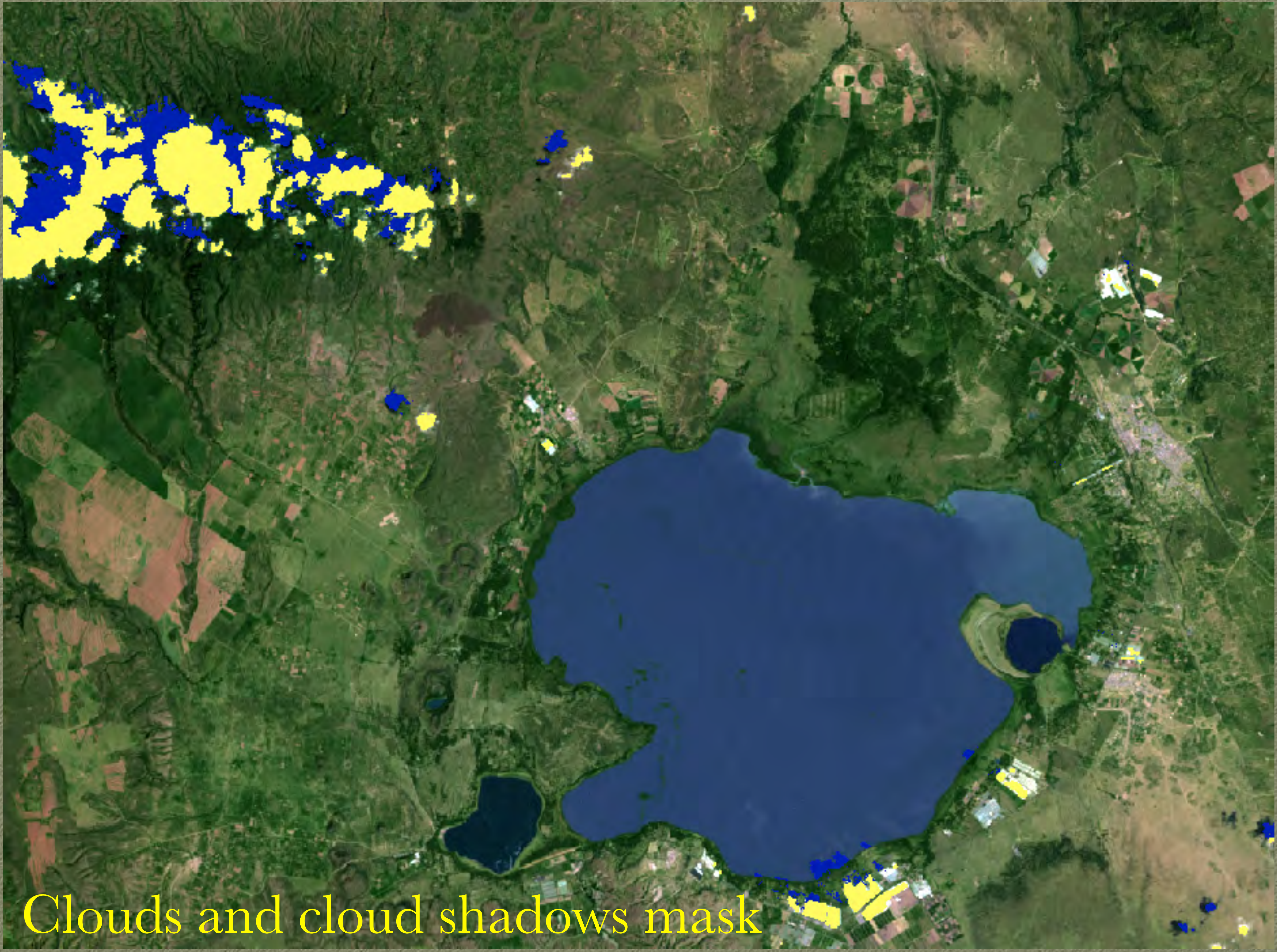
Tasseled Cap Normalized Difference Water Index)

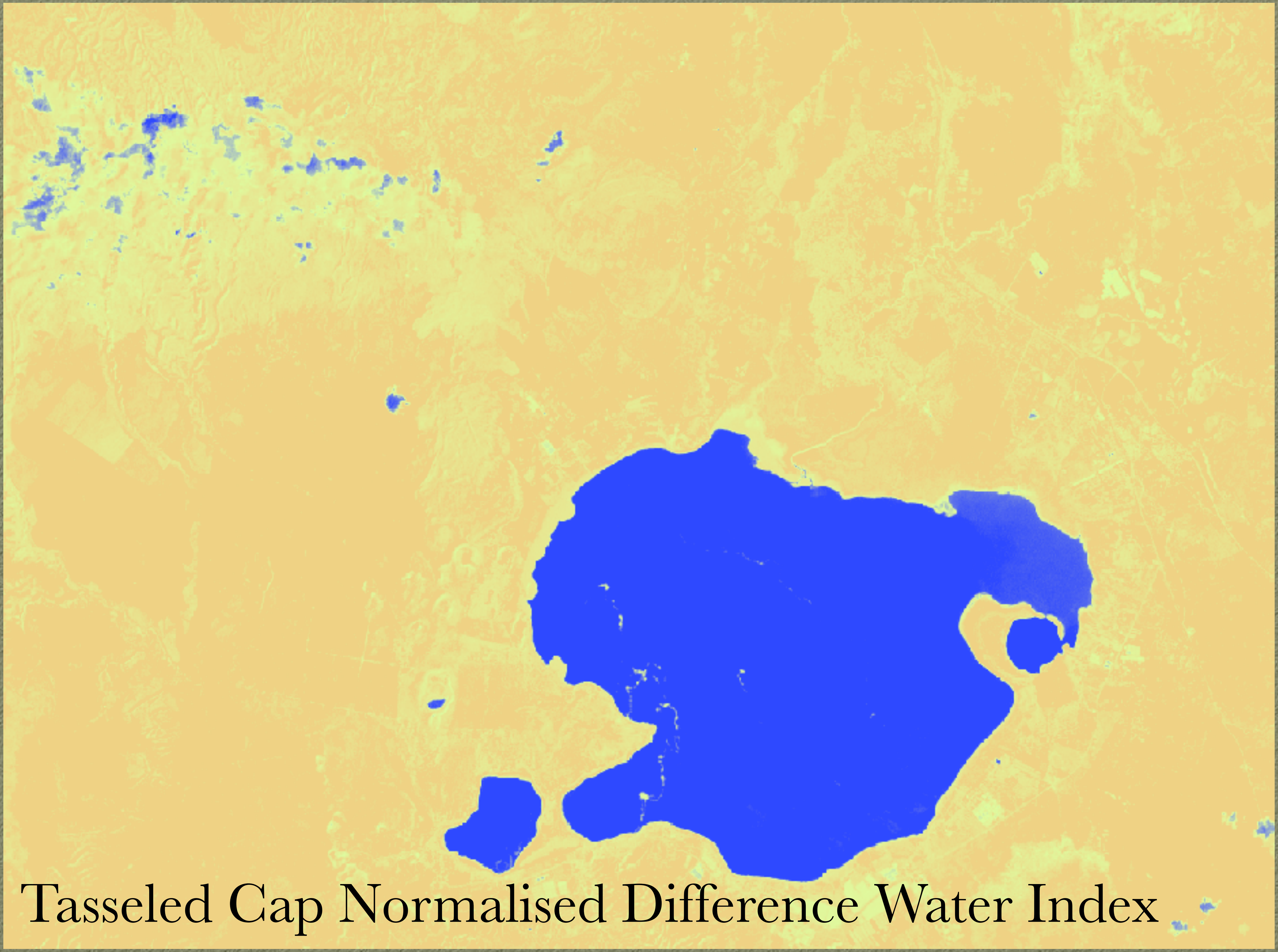


Tasselled Cap Normalized Difference Cloud Index

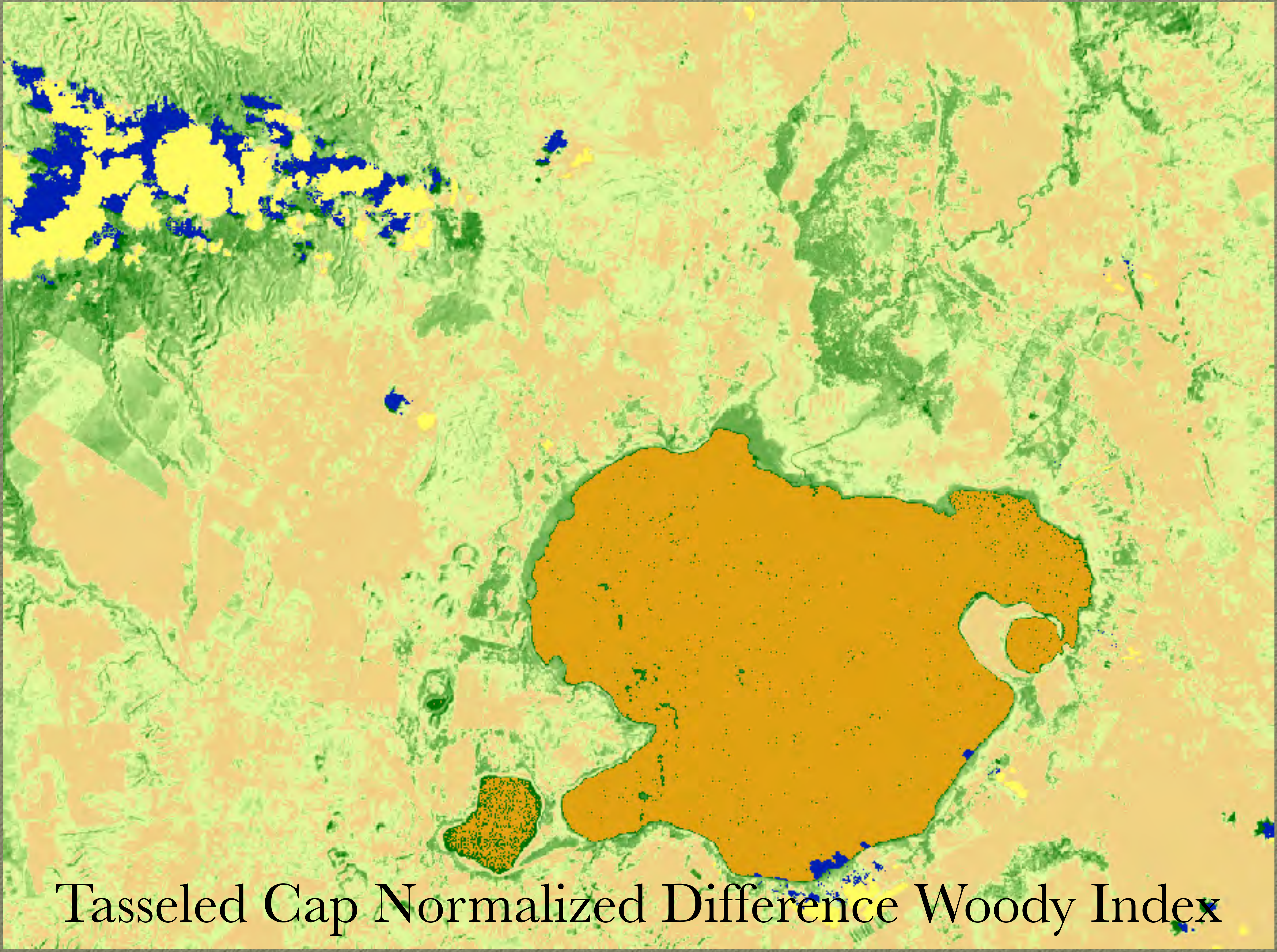

Thermal emissivity (surface skin temperature)


TCNDCI with natural color image as backdrop

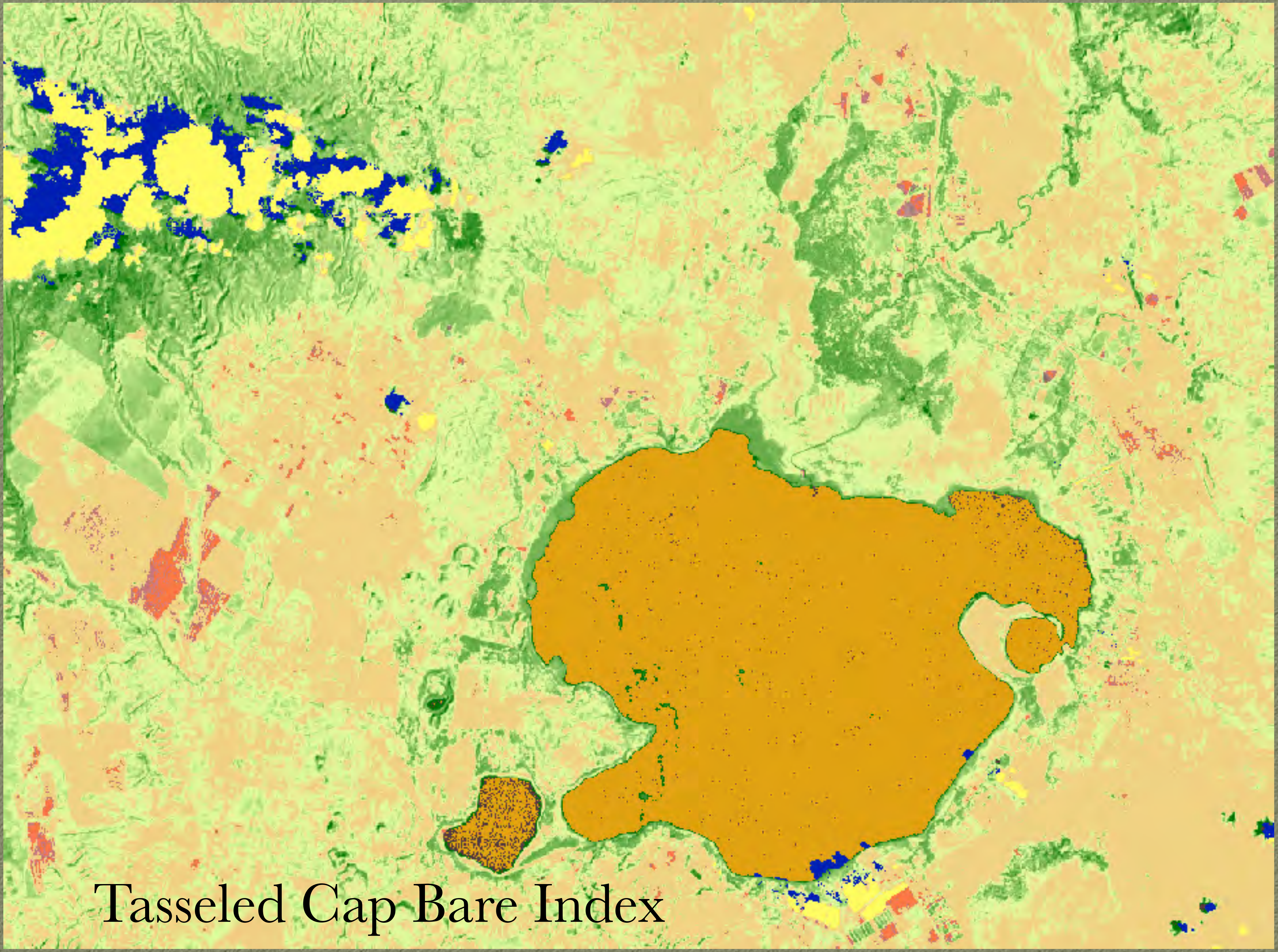

Clouds and cloud shadows mask



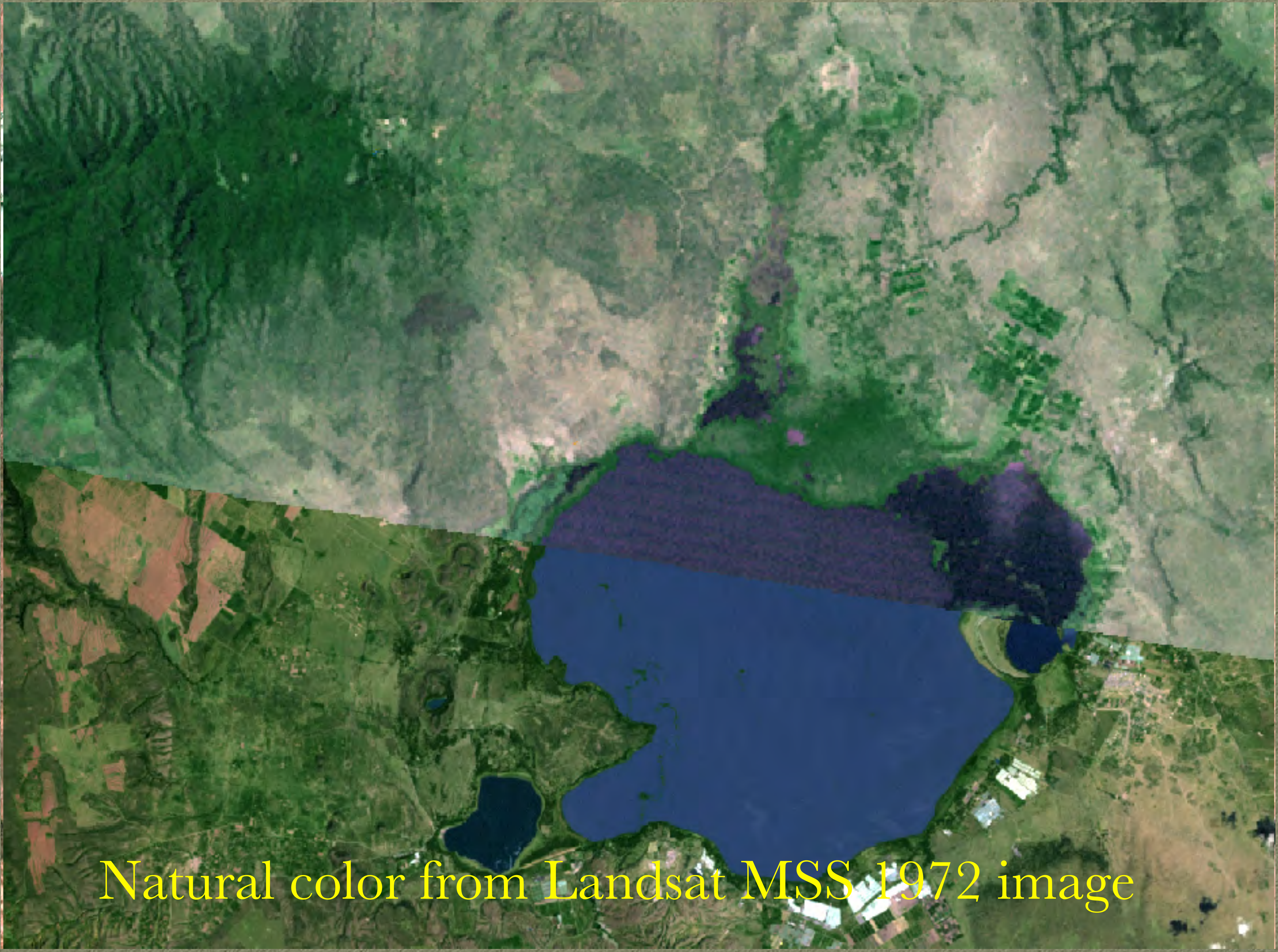
Tasseled Cap Normalised Difference Water Index



Tasseled Cap Normalized Difference Woody Index


Tasseled Cap Bare Index

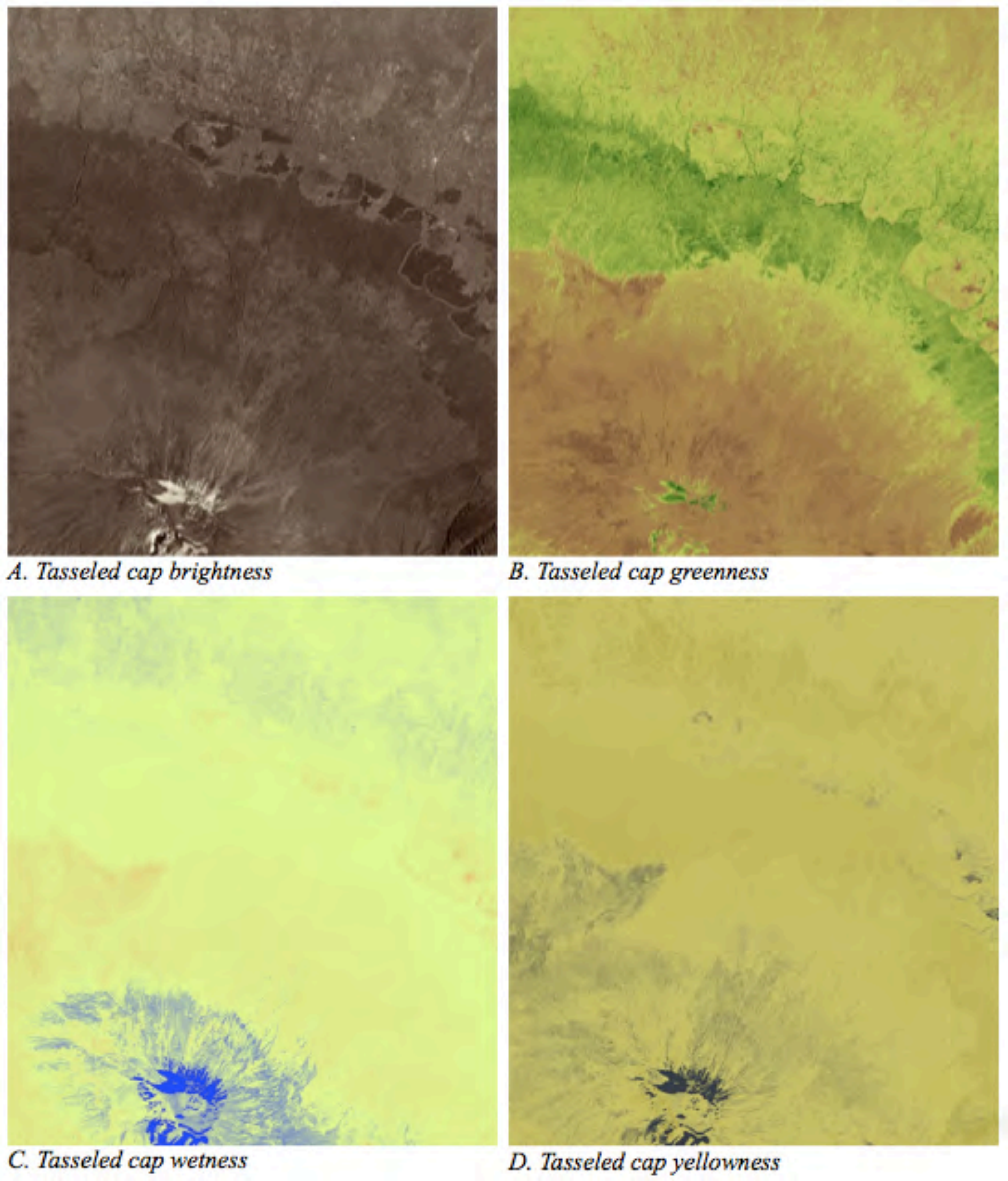

Soil spectral signal after vegetation spectral unmixing


Natural color from Landsat MSS 1972 image


Tasseled Cap Brightness from 1972 and 2001

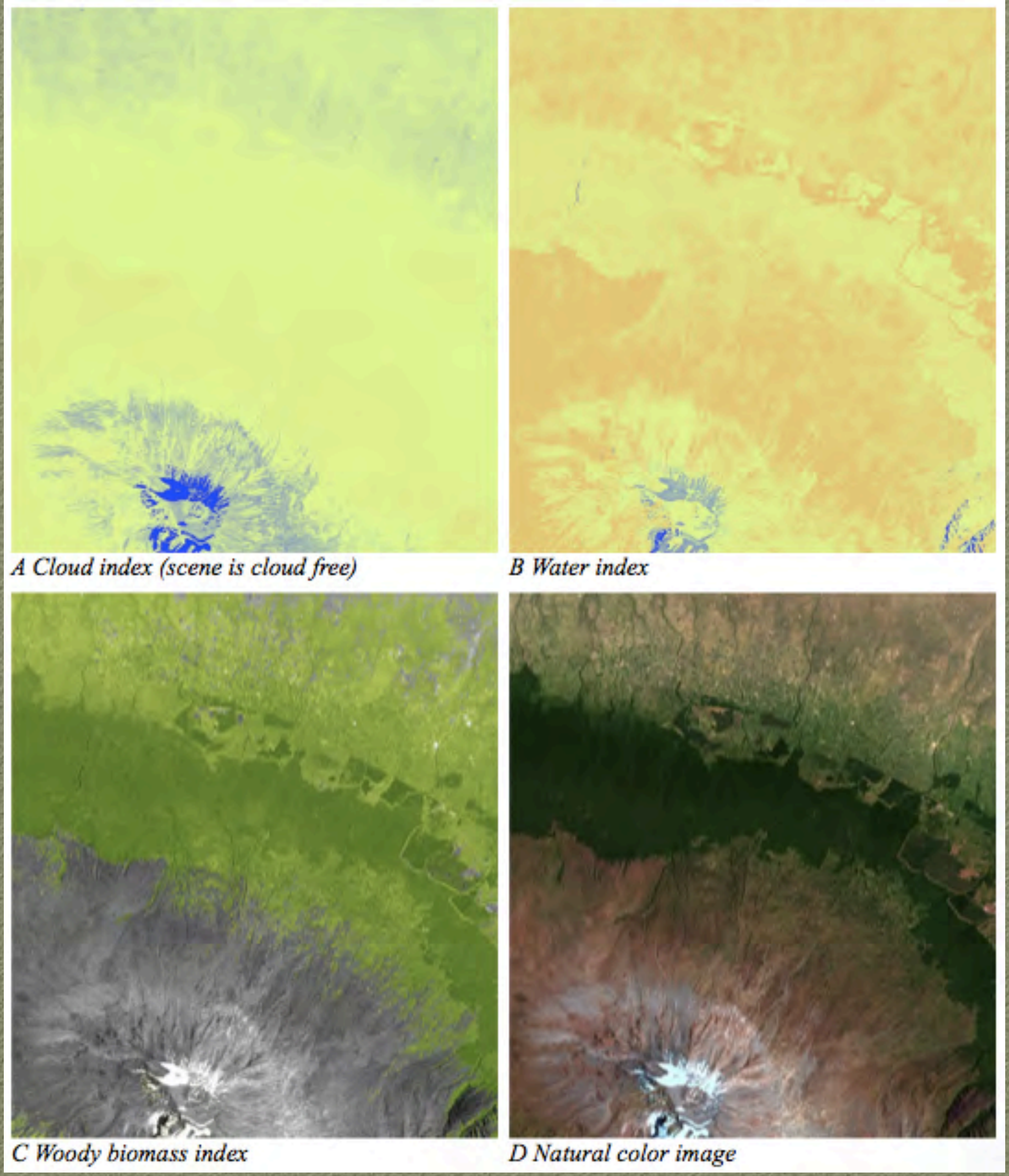
PART 4 Applications

Mount Kilimanjaro



A. Tasseled cap brightness
B. Tasseled cap greenness
C. Tasseled cap wetness
D. Tasseled cap yellowness

Mount Kilimanjaro



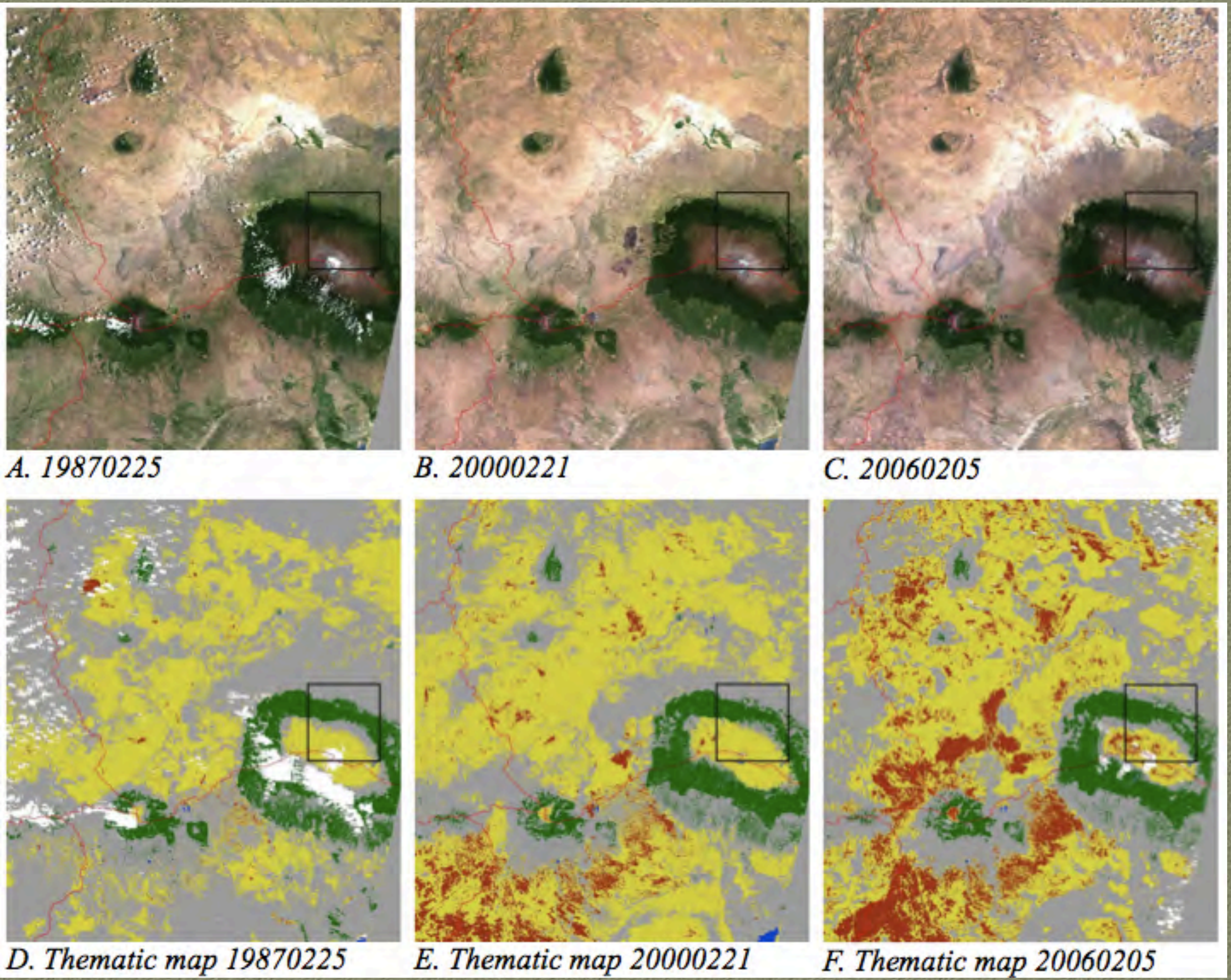
A Cloud index (scene is cloud free)

B Water index

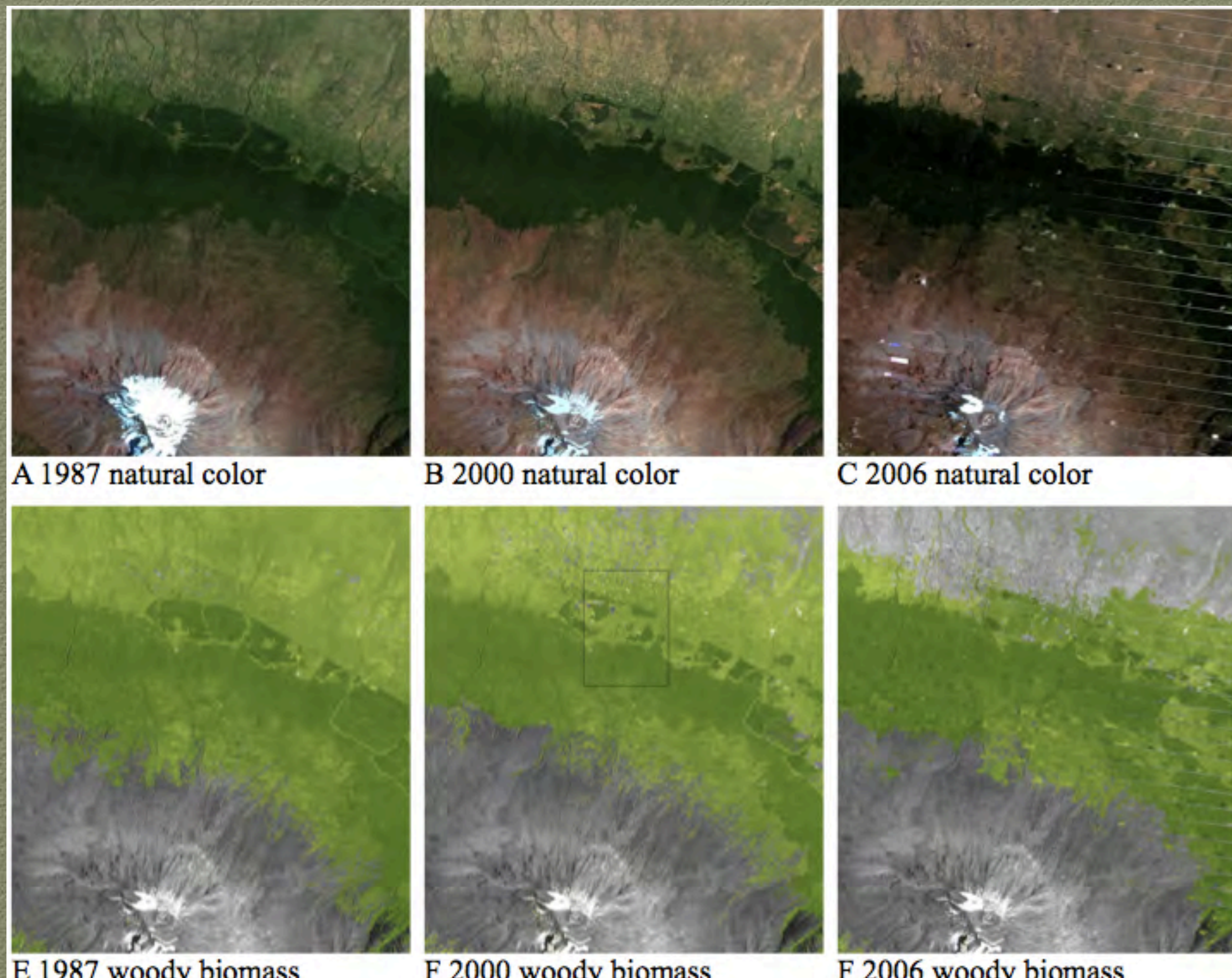
C Woody biomass index

D Natural color image

Mount Kilimanjaro



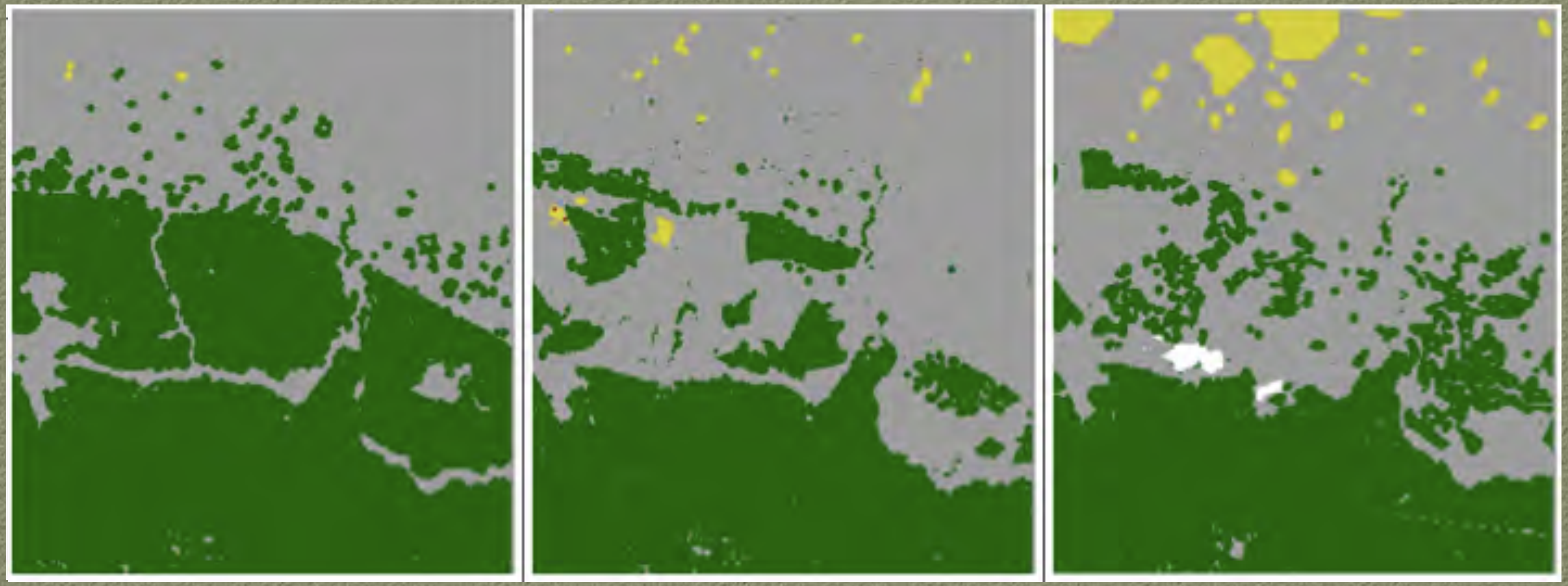
Mount Kilimanjaro



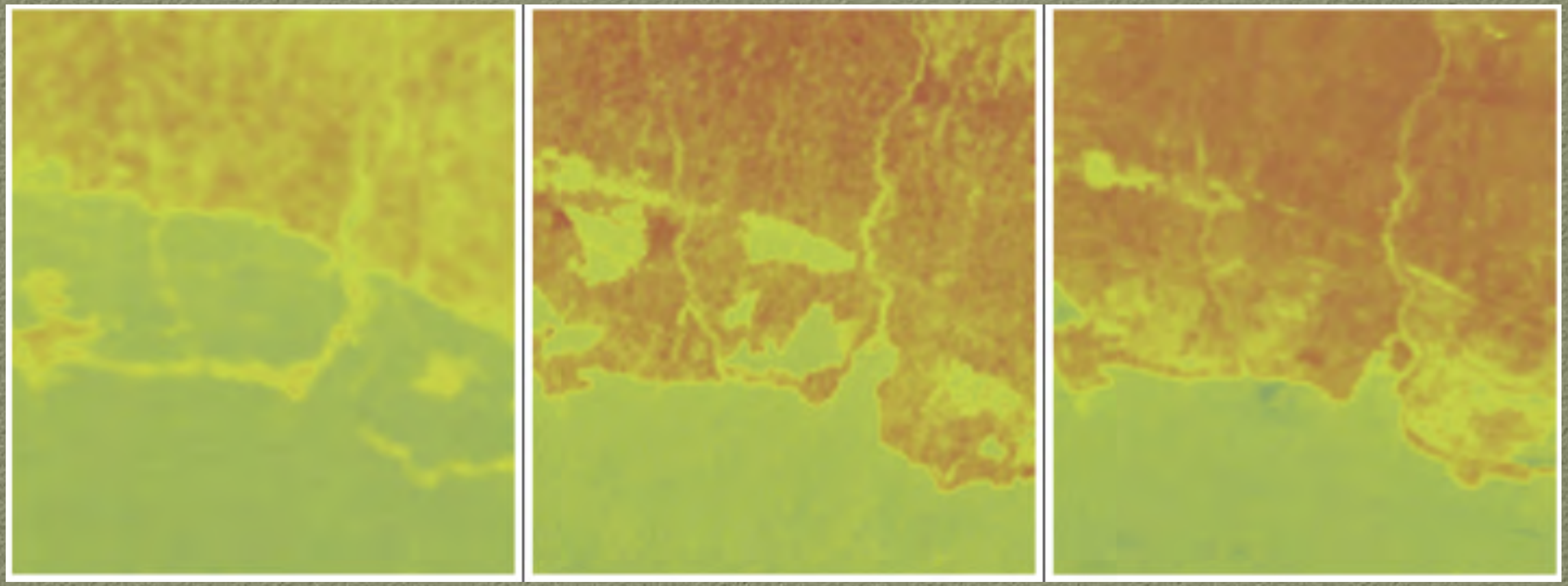
A 1987 natural color
B 2000 natural color
C 2006 natural color
E 1987 woody biomass
F 2000 woody biomass
F 2006 woody biomass

Mount Kilimanjaro

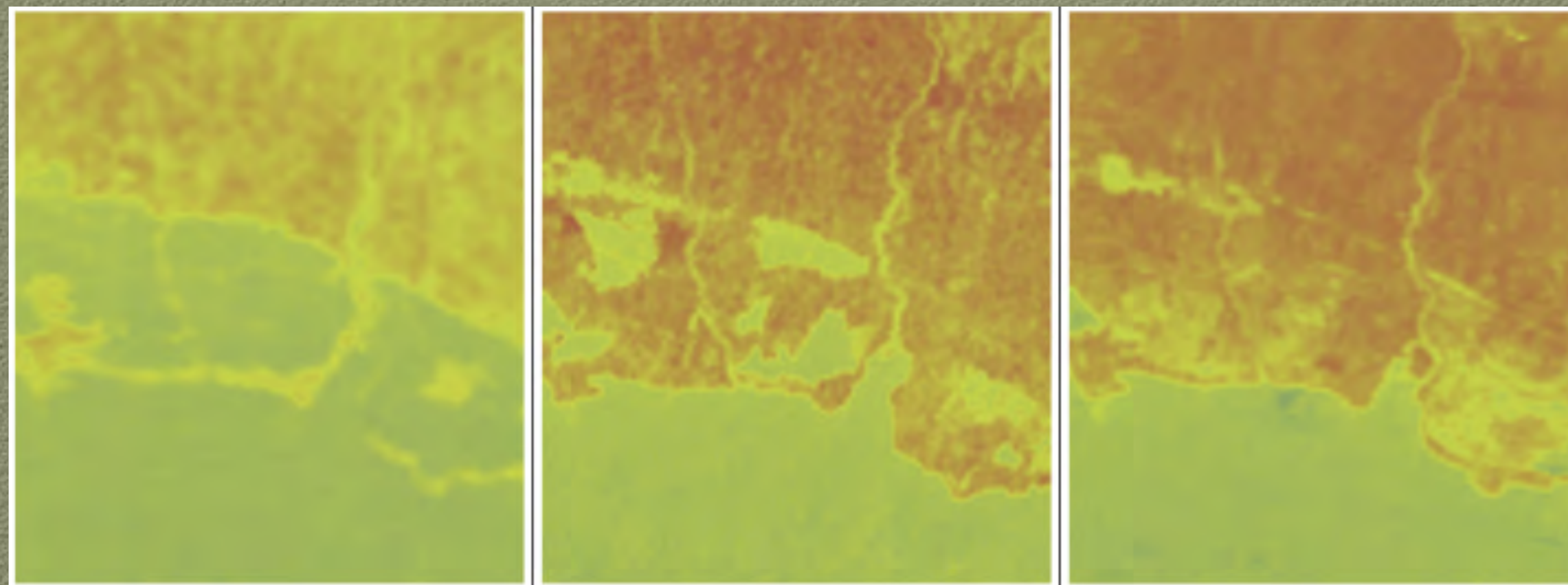
Mount Kilimanjaro



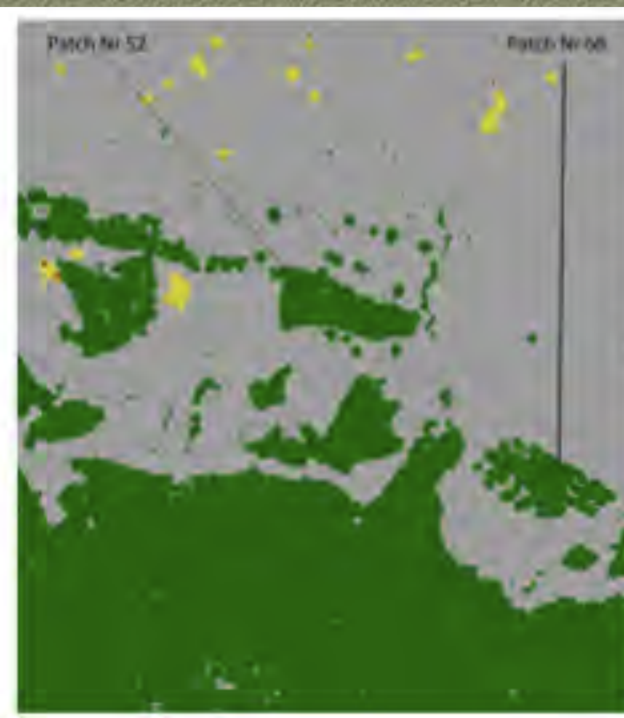
Mount Kilimanjaro



Mount Kilimanjaro

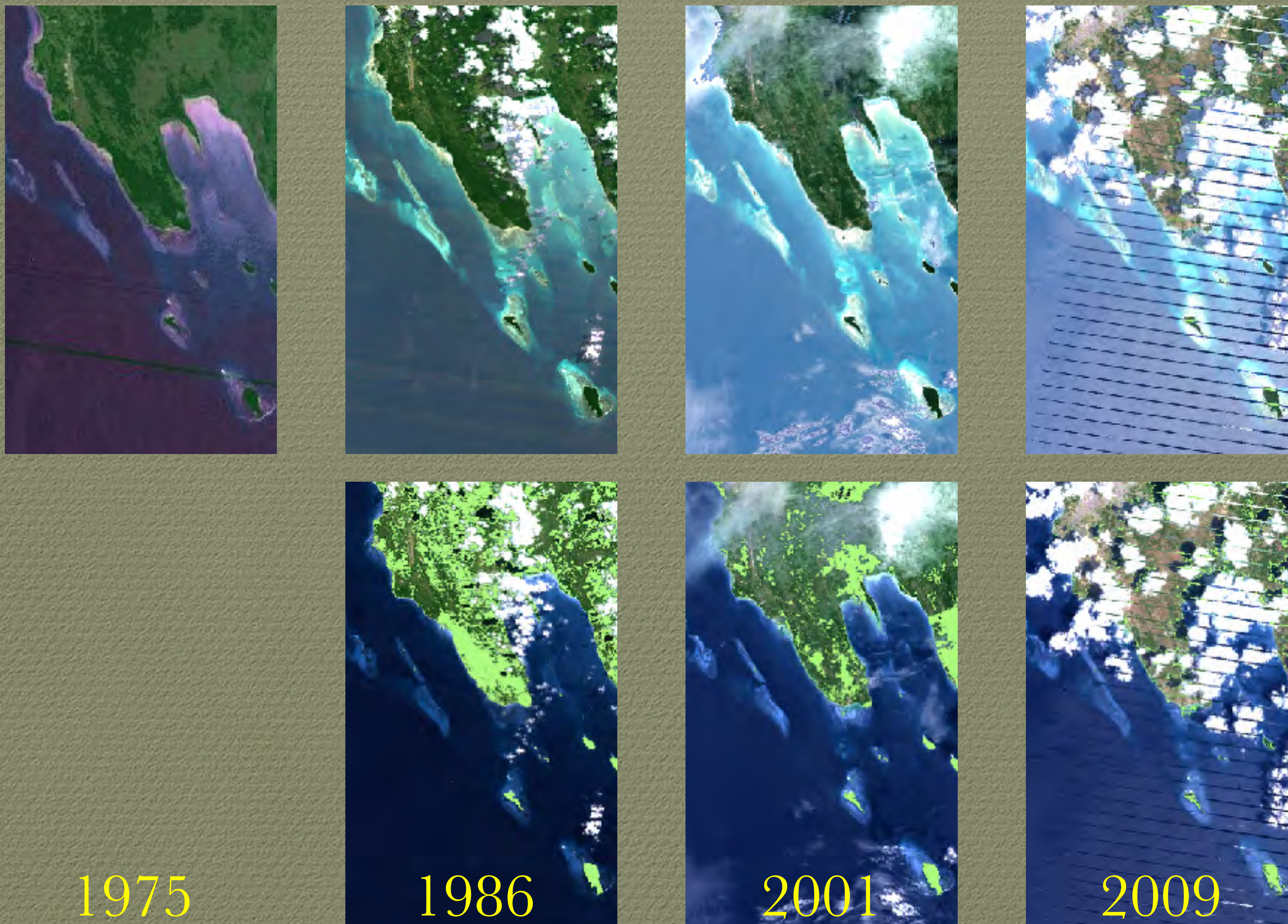


Patch Nr 52
Area (ha): 83.256
Perimeter (m): 6270.000
Shape Index: 1.718
Fractal Dimension: 1.079
Core Area (ha): 56.695
Num Core Areas: 1
Core Area Index (%): 68.098



Patch Nr 86
Area (ha): 73.590
Perimeter (m): 10944.000
Shape Index: 3.189
Fractal Dimension: 1.172
Core Area (ha): 32.003
Num Core Areas: 10
Core Area Index (%): 42.488

Zanzibar



Rwenzori

Lake Tanganyika
Tanzania
Mount Kilimanjaro
Lake Victoria
Lake Edward
Mount Kenya
Map
area
Kenya
Mount Elgon
Lake Kyoga
Mount Rwenzori
Lake Albert
DRC
N
Uganda
Lake Turkana

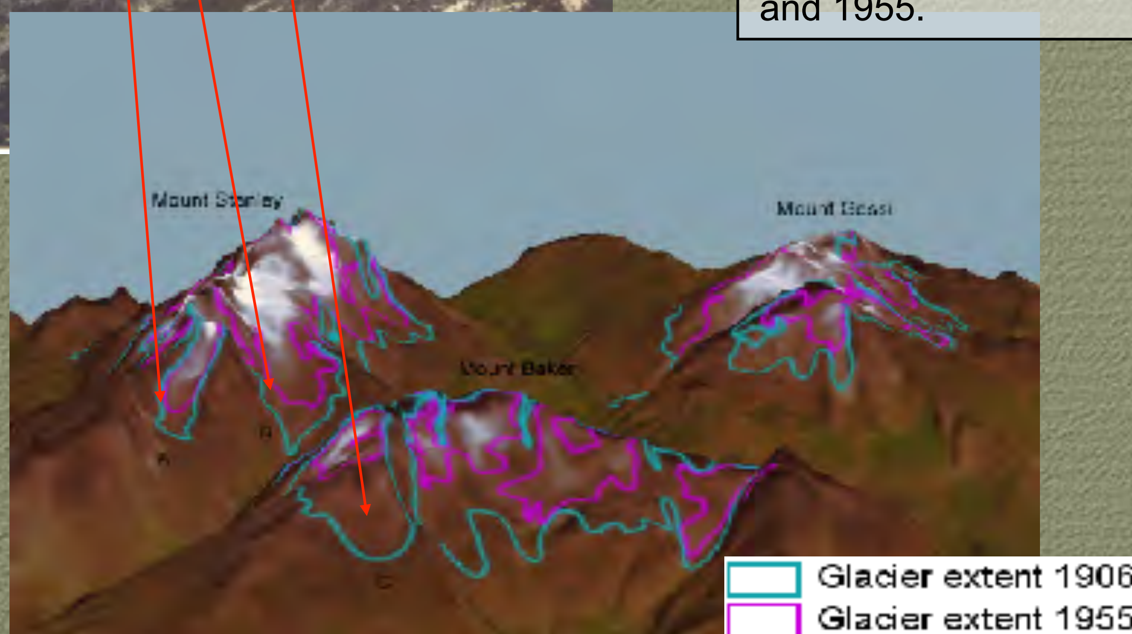
Rwenzori


Lake Tanganyika
Tanzania
Mount Kilimanjaro
Lake Victoria
Lake Edward
Map
area
ke Kyoga
Mount Rwenzori
Lake Albert
DRC
N

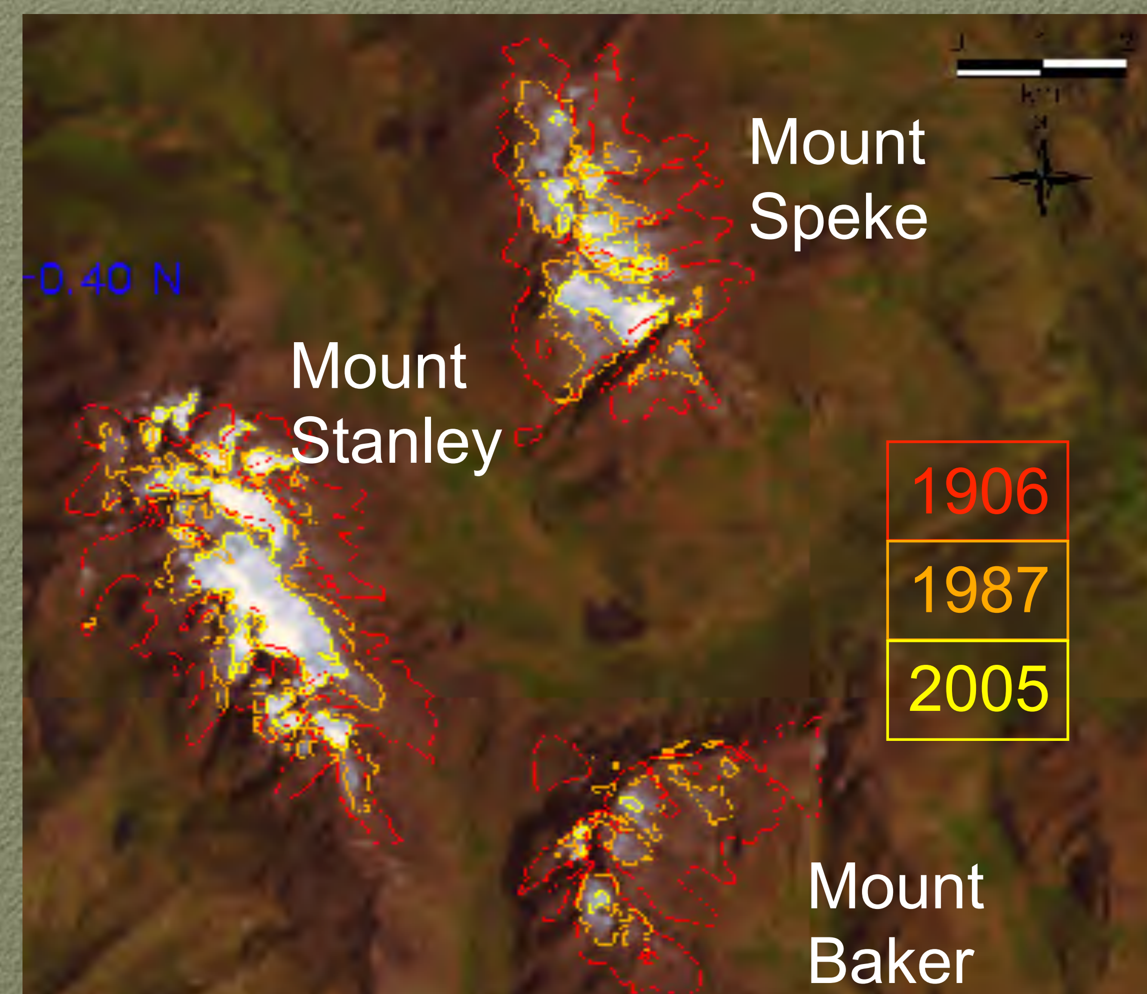
Rwenzori

Glaciers in the Rwenzori Mountains: a reinterpretation

Photograph by Sella taken the 12th of July 1906 from Stairs Peak, showing Mount Baker and Mount Stanley.

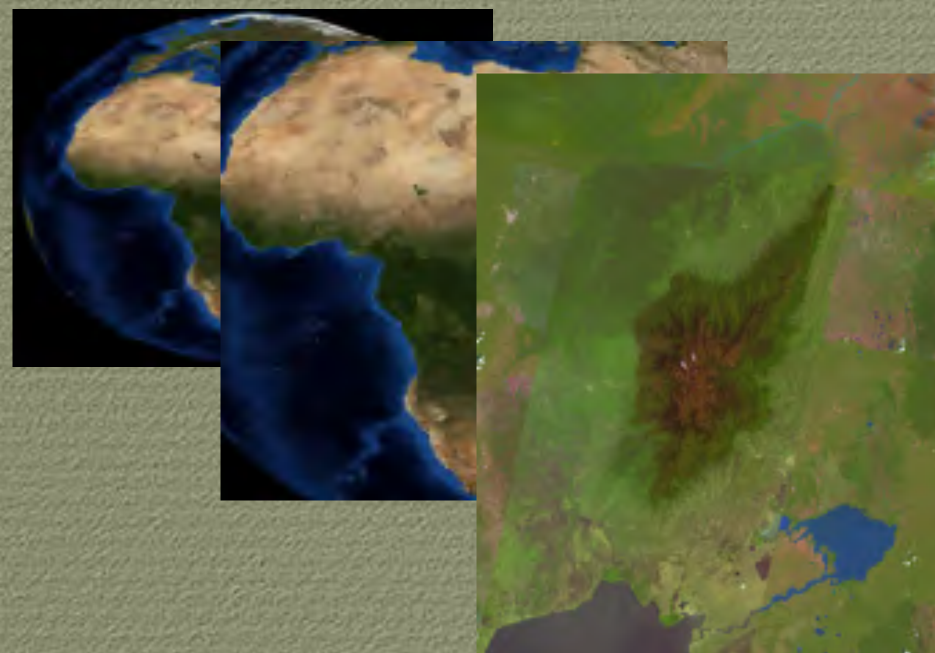


Satellite generated image of the peaks of the Rwenzori Mountains (2005), also showing glacial extents in 1906 and 1955.



Rwenzori

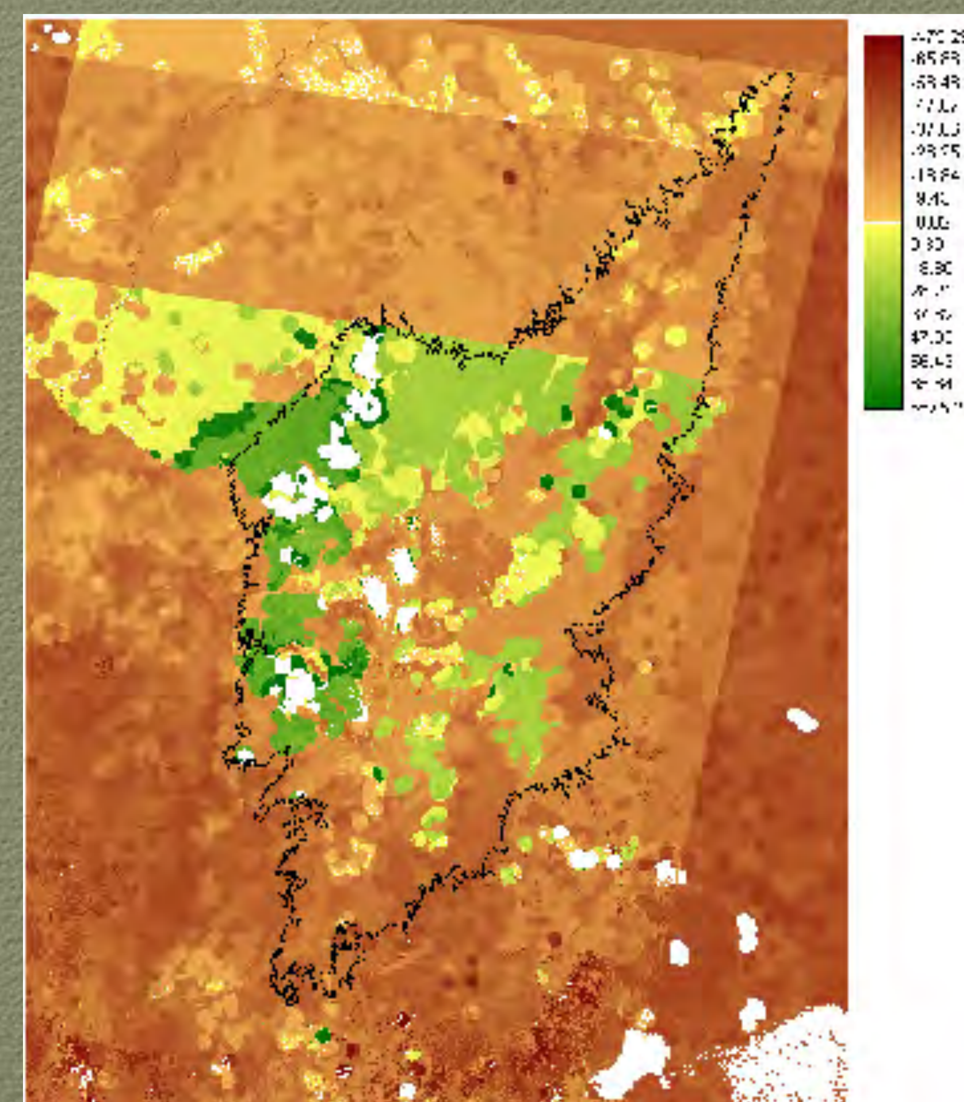
Driving forces contributing to glacier retreat



a) Global changes in temperature and atmospheric circulation patterns.

b) Continental drying (less precipitation and more sunshine)

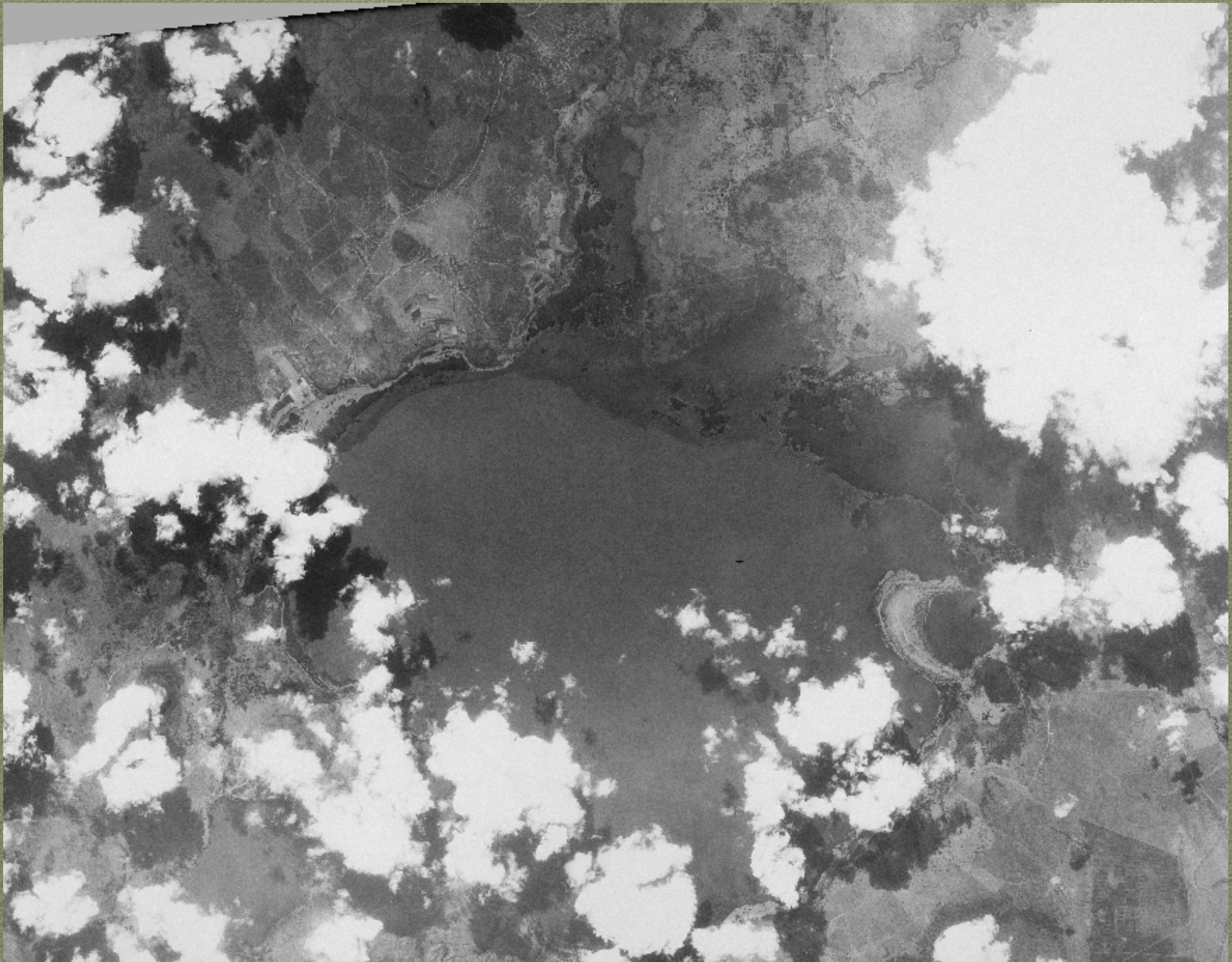
c) Local changes in land use and land cover



Landcover changes – Adjusted NDVI trend 1973-2005

Lake Naivasha

Lake Naivasha



Lake Naivasha

Ivory Coast

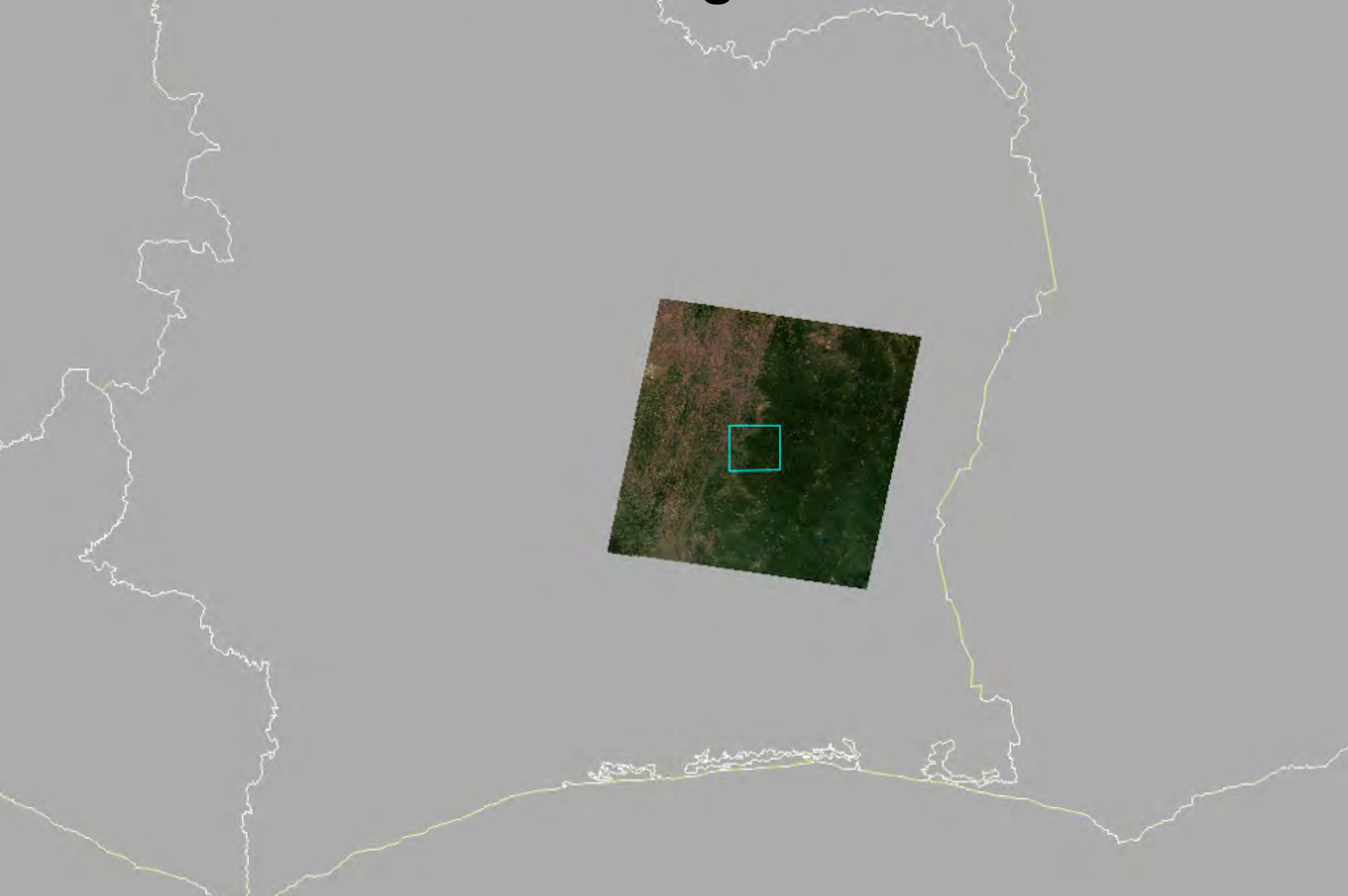
Vegetation and land cover changes in the **cocoa** belt in **Ivory Coast**

using time series of high resolution satellite images

The illustration site was chosen to represent the transition zone between open land and forest.

Thomas Gumbricht, ICRAF

Landsat TM image from 1988



Thomas Gumbricht, ICRAF

Landsat TM image from 1988

The image is corrected for sun-earth geometry and atmospheric disturbances. The colors are then derived from the corrected image bands.

The reflectance data of the image can be used for mapping biophysical ground conditions - notably in combination with a spectral library derived from ground sampling in the region of study.

Landsat TM image from 2002

This image is taken 14 years later, but in the same season (December). The anniversary image pair can be used for studying changes in vegetation (e.g. forests and tree cover) and other land cover changes.

Let us look at some changes that can be easily detected from this image pair....

Thomas Gumbricht, ICRAF

Landsat TM image from 2002

This image is taken 14 years later, but in the same season (December). The anniversary image pair can be used for studying changes in vegetation (e.g. forests and tree cover) and other land cover changes.

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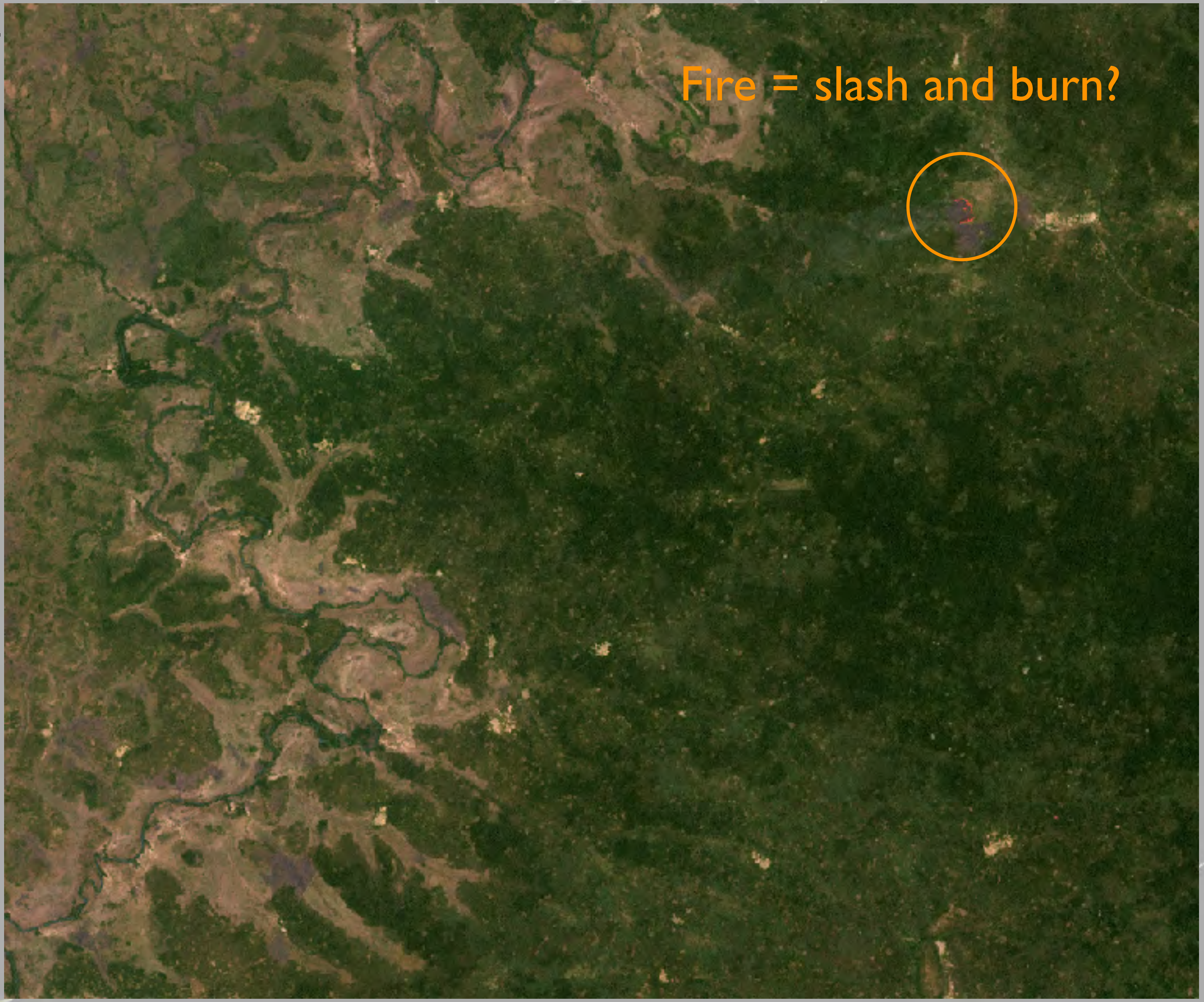

Thomas Gumbricht, ICRAF

Landsat TM image from 2002

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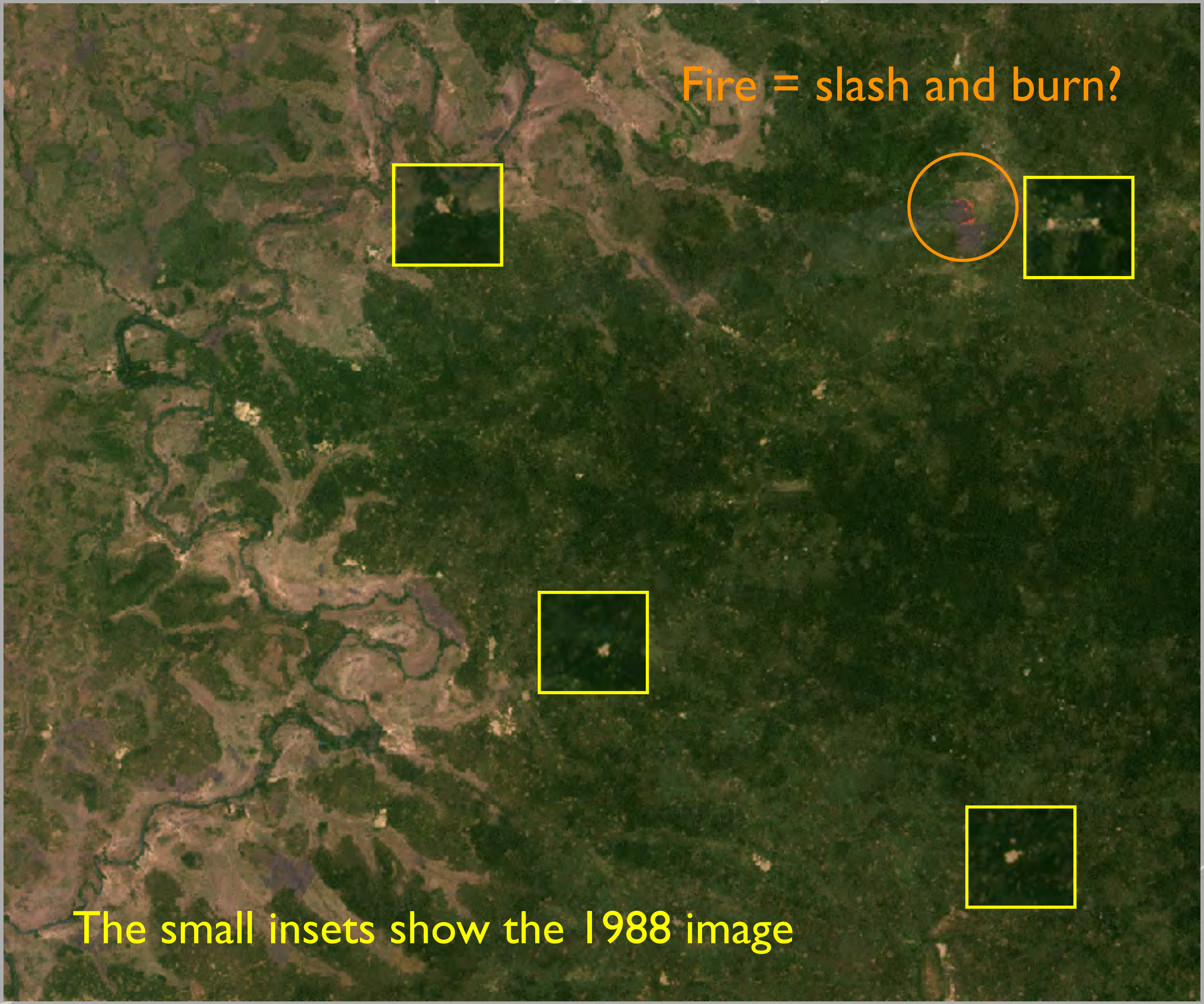

Thomas Gumbricht, ICRAF

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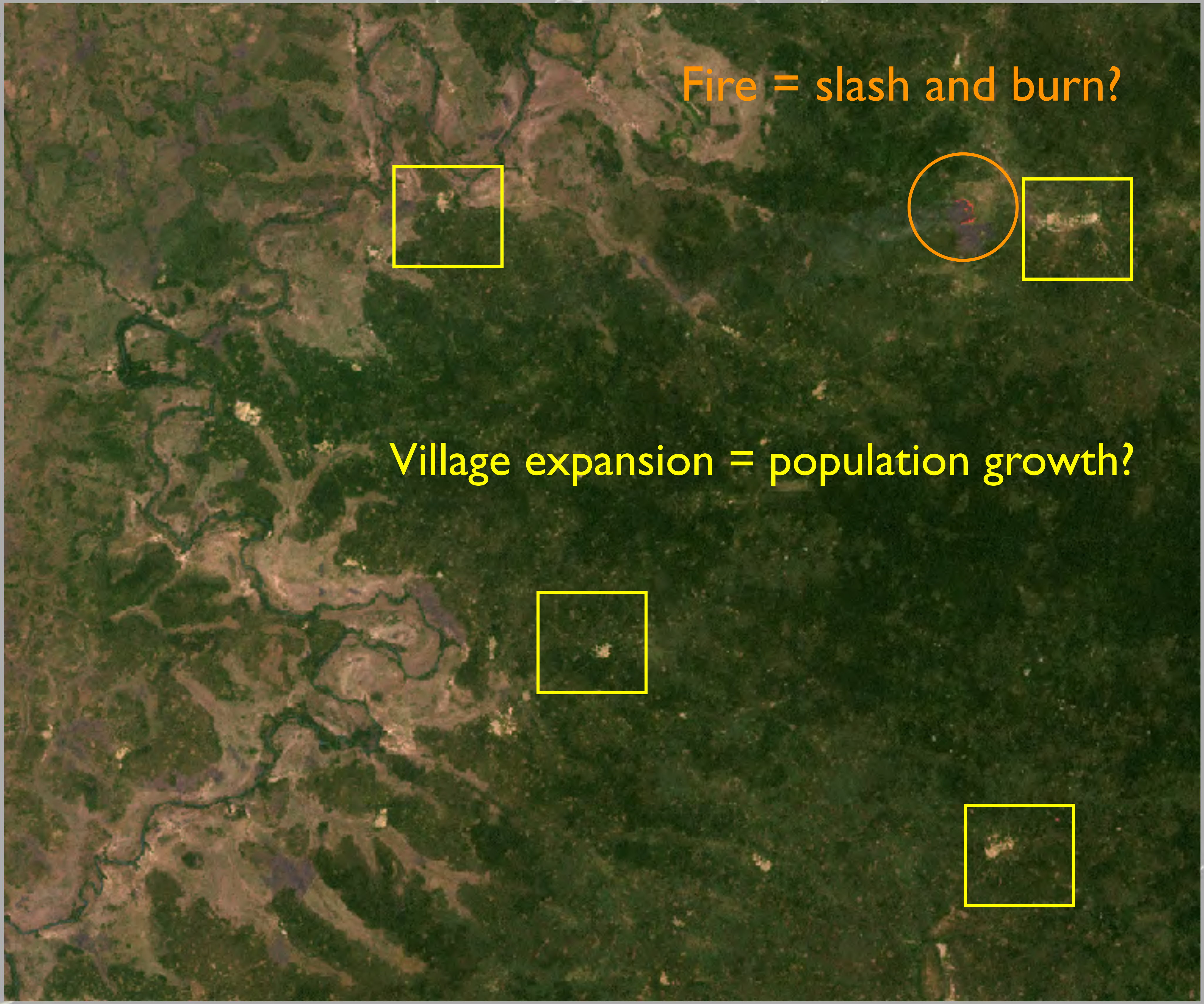
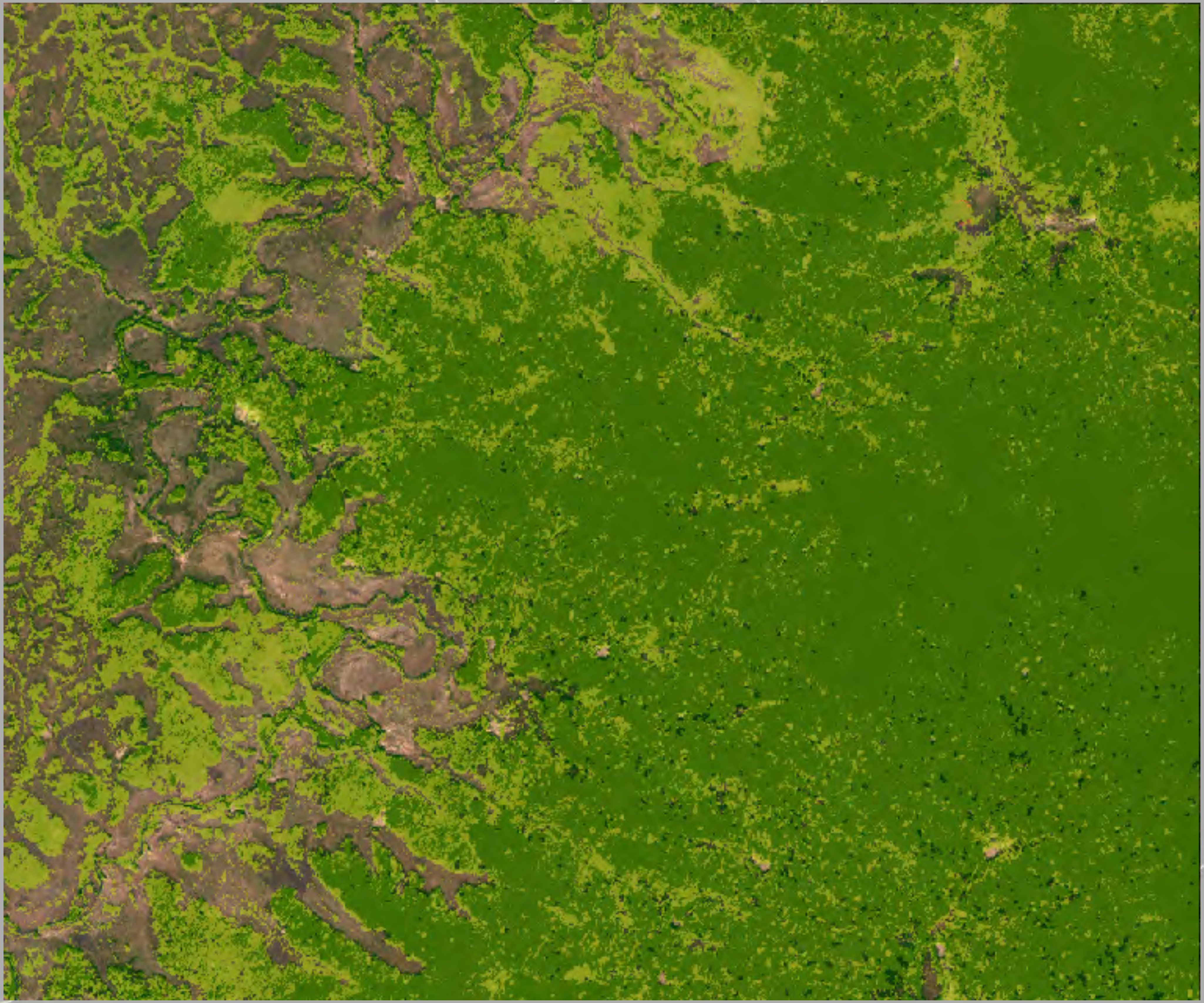


Thomas Gumbricht, ICRAF

Forest losses from1988 to 2002

This image illustrates the forest cover in 1988 (green-yellow) compared with 2002 (green). the yellowish areas were forested in 1988, but not in 2002.

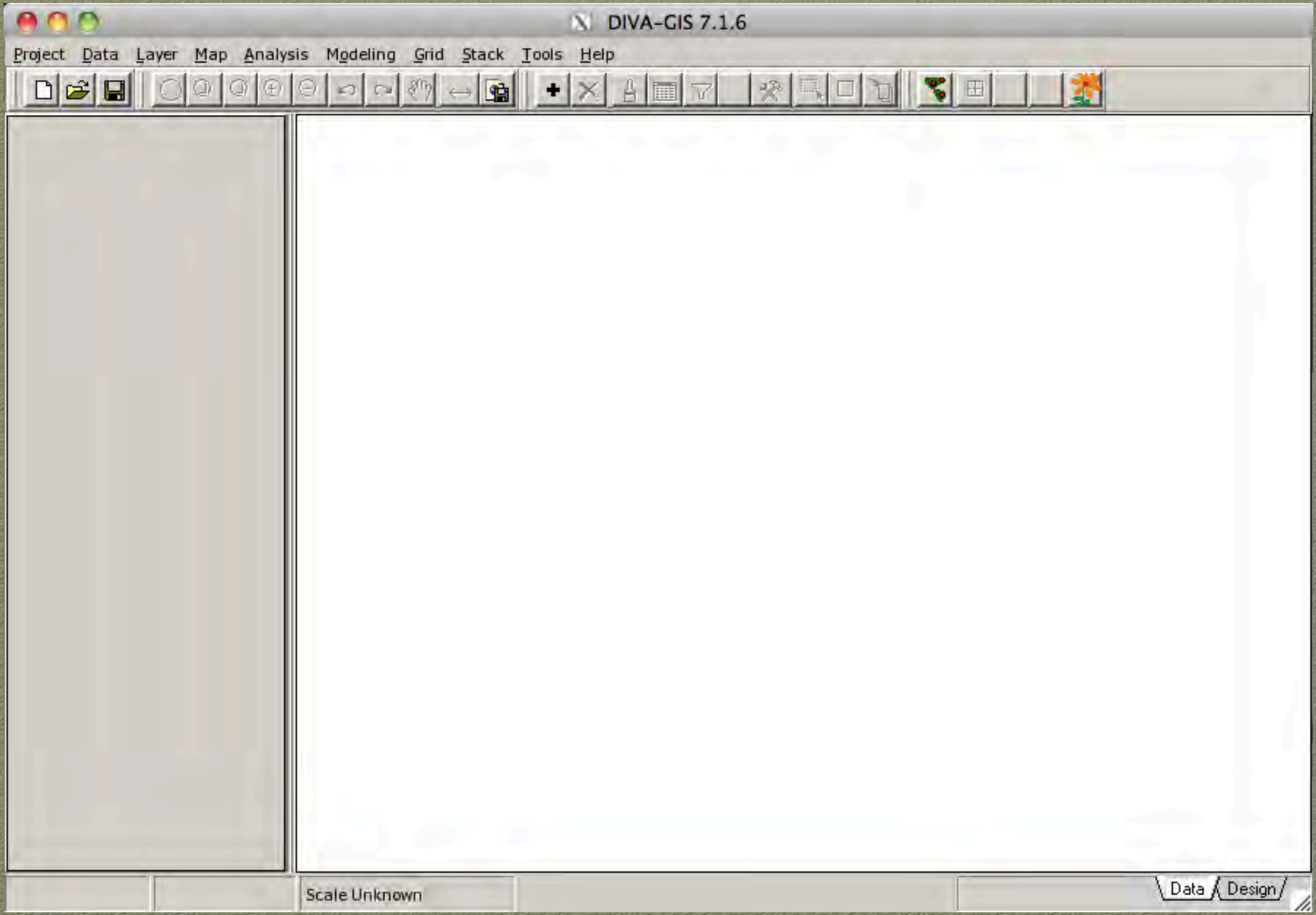


The forest cover is calculated from global standards in forest reflection. To evaluate the accuracy of the forest cover maps, site specific field data is needed. It would then also be possible to estimate the losses in biomass - and in carbon storage.

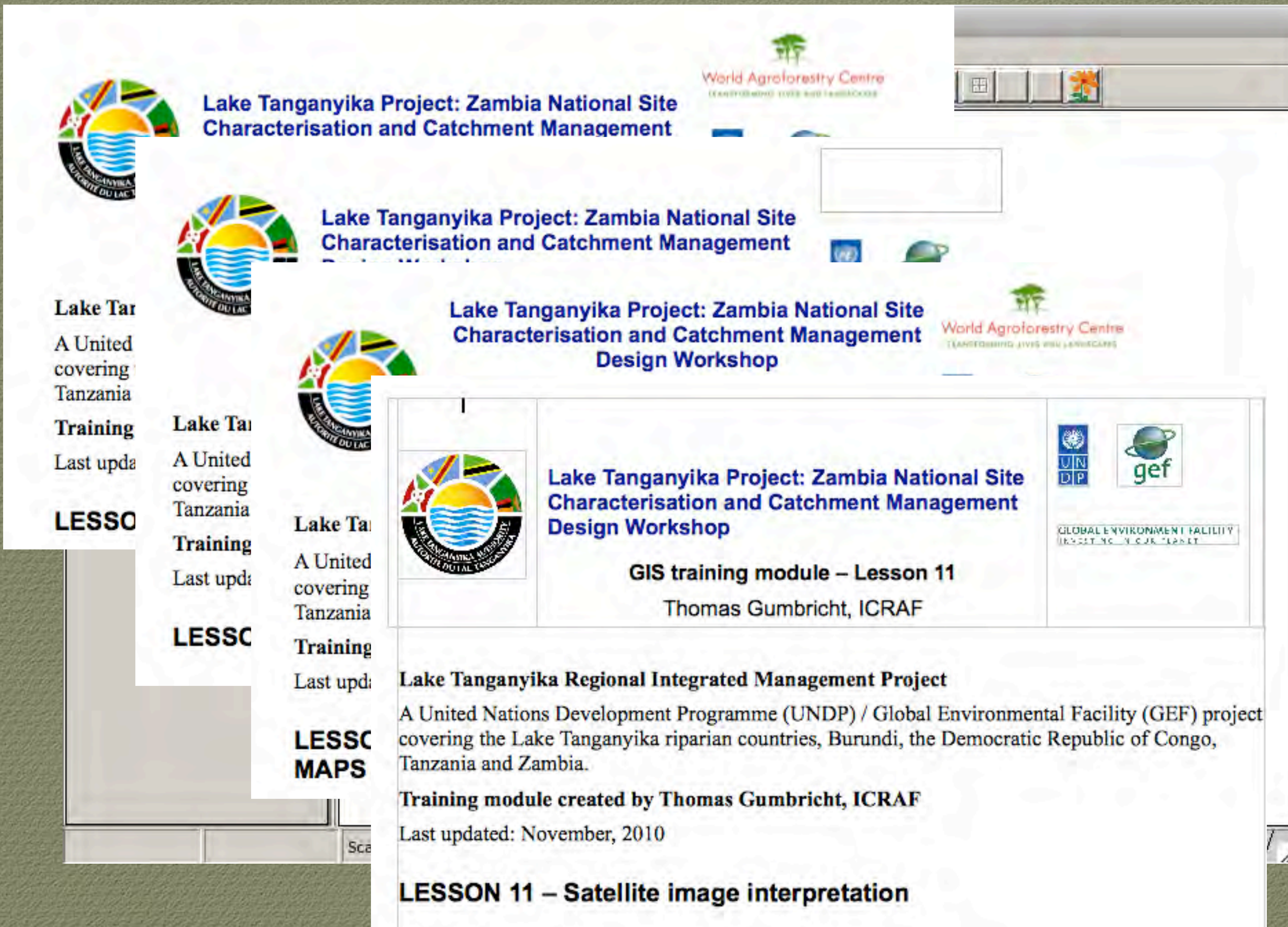
Thomas Gumbricht, ICRAF

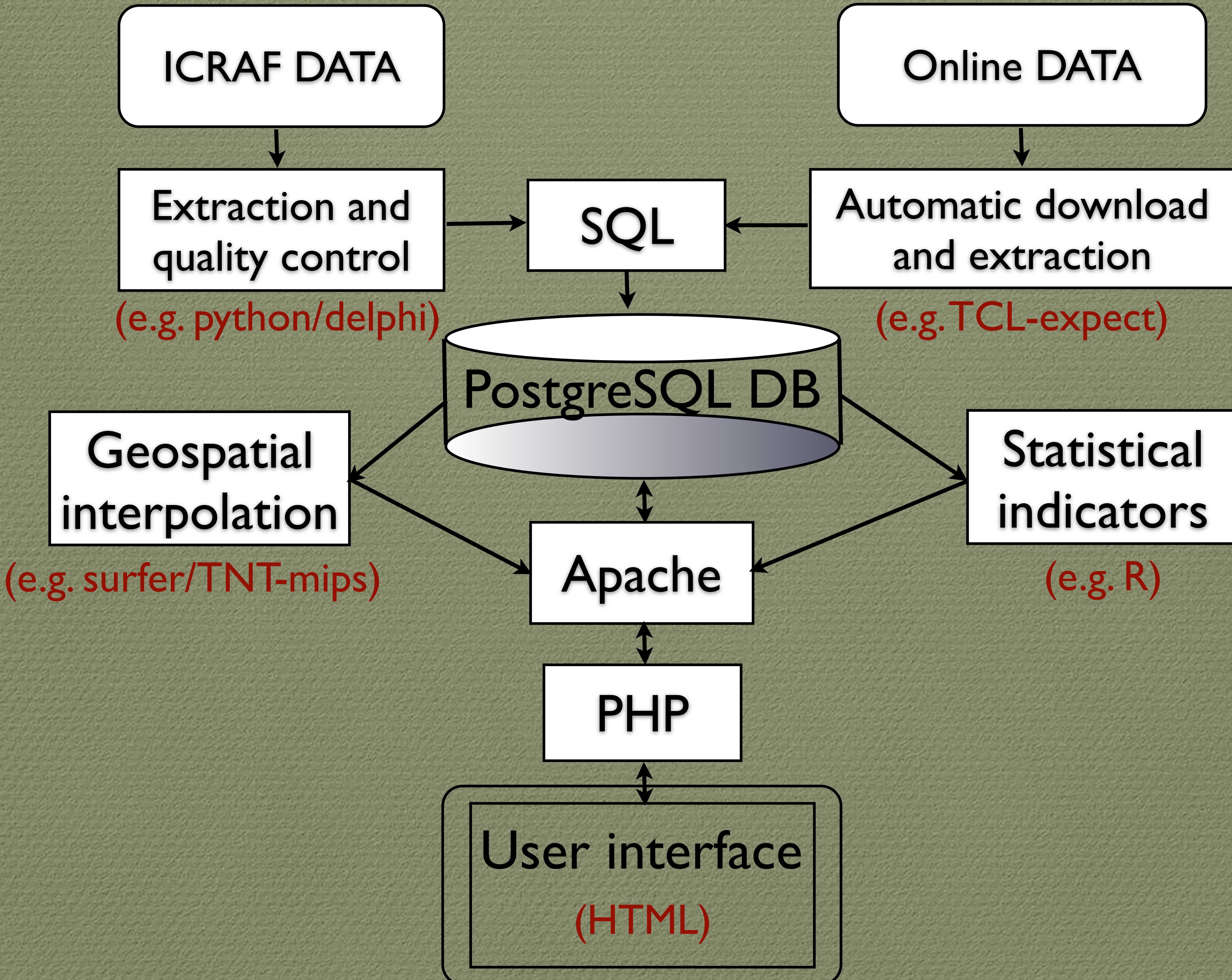
PART 5 Sharing and Dissemination

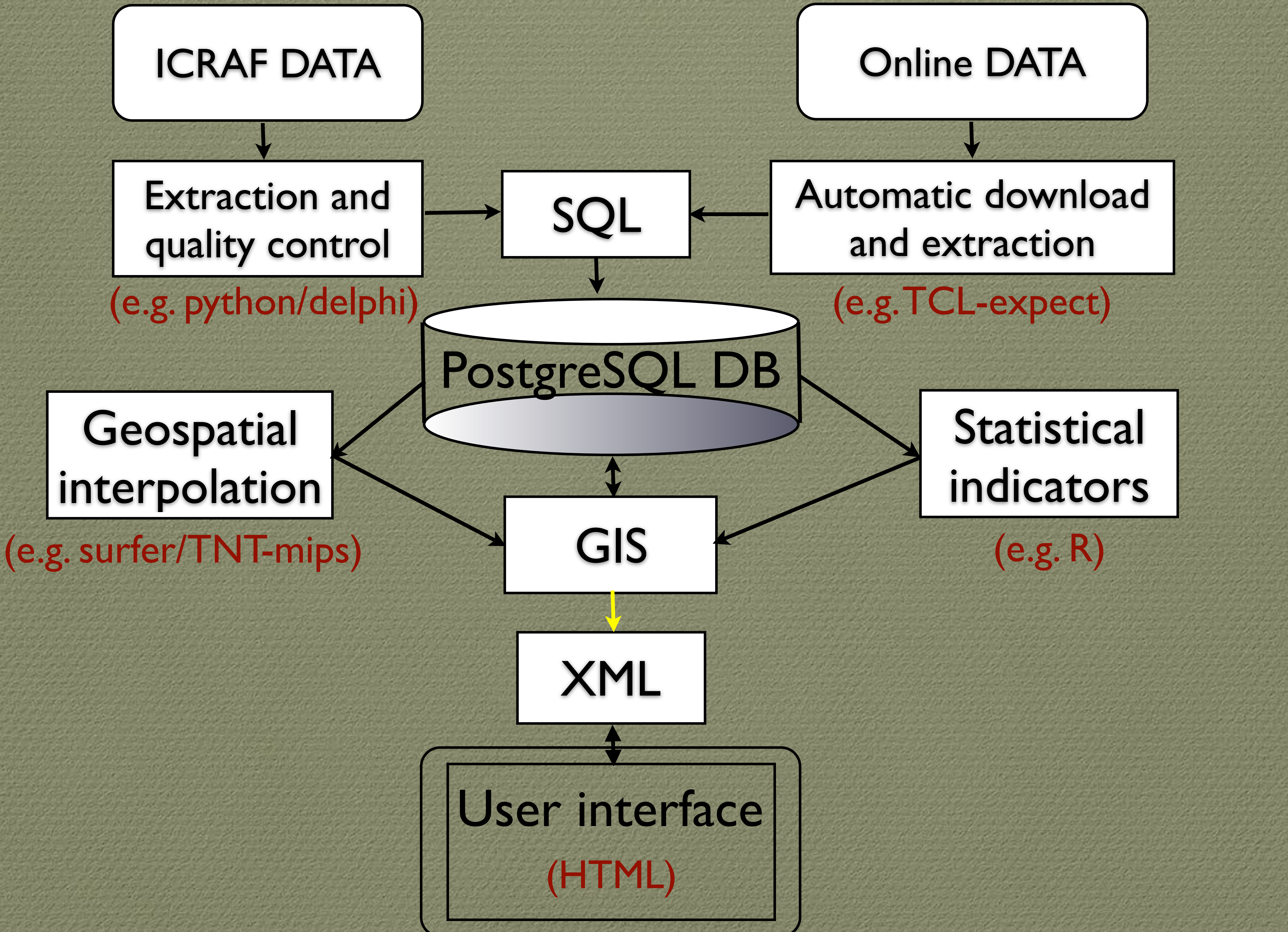
Freeware GIS



Freeware GIS




ICRAF DATA
Online DATA
Extraction and quality control
(e.g. python/delphi)
SQL
Automatic download and extraction
(e.g. TCL-expect)
PostgreSQL DB
Geospatial interpolation
(e.g. surfer/TNT-mips)
Statistical indicators
(e.g. R)
Apache
PHP
User interface
(HTML)



ICRAF DATA
Online DATA
Extraction and quality control
(e.g. python/delphi)
SQL
Automatic download and extraction
(e.g. TCL-expect)
PostgreSQL DB
Geospatial interpolation
(e.g. surfer/TNT-mips)
Statistical indicators
(e.g. R)
GIS
XML
User interface
(HTML)