Image transformations

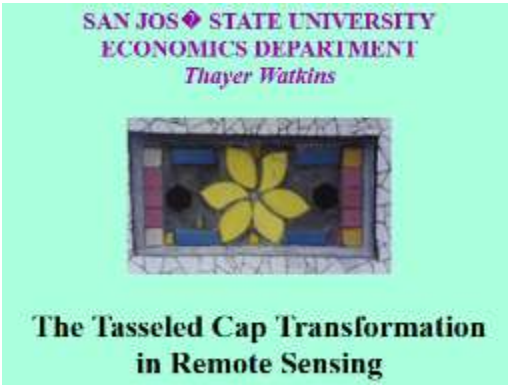
Digital Numbers may be composed of three elements:

- **Atmospheric interference (e.g. haze) – 'ATCOR'**
- **Illumination (angle of reflection) - transforms**
- **Albedo (surface cover)**

Most bands are variably affected by a. and b. but it is usually c. we want to study / interpret in remote sensing

Image transformations:

Converting multi-band datasets into a smaller channel combination reducing dimensionality, that retains most of the original data but enhances interpretability.



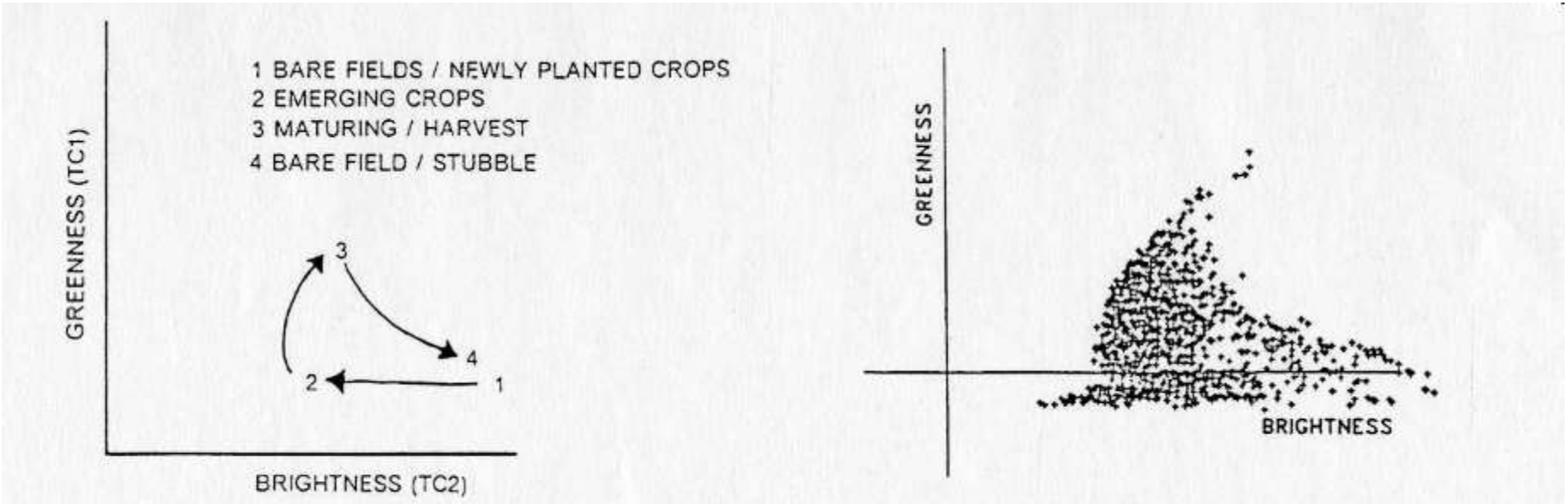
Tasseled Cap: the conversion of DNs readings in a set of bands into weighted sums of **separate channels**. TC1 measures the brightness of each pixel in the scene. The other composite values are linear combinations of the values of the separate channels, but some of the weights are negative and others positive. One of these represents the degree of **greenness** of the pixels and another the **yellowness** of vegetation, or perhaps the **wetness** of the soil. (Landsat MSS or TM)

https://www.sjsu.edu/faculty/watkins/tassel.htm

Tasseled Cap transformation

The technique was named after the pattern of spectral change of agricultural crops during senescence, plotting brightness (visible) against greenness (NIR). The sequence is:

1. Bare fields / newly planted crops - high brightness, low greenness (spring)
2. Plant Growth - <-<- brightness (early summer)
3. Maturity: -> -> greenness (late summer)
4. Senescence (harvest) - bare field/stubble: <-<-greenness, ->-> brightness (Fall)



Kauth, R. J. and Thomas, G. S., 1976, The tasseled cap --a graphic description of the spectral-temporal development of agricultural crops as seen in Landsat, in Proceedings on the U.S. Department of the Interior 9 U.S. Geological Survey Symposium on Machine Processing of Remotely Sensed Data, West Lafayette, Indiana, June 29 -- July 1, 1976, 41-51.

Tasseled Cap transformation

ArcMap 10.3

|

The Tasseled Cap (Kauth-Thomas) transformation is designed to analyze and map vegetation and urban development changes detected by satellite sensors. It is known as the Tasseled Cap transformation due to the data shape.

It was developed in 1976 by R.J. Kauth and G.S. Thomas of the Environmental Research Institute of Michigan (ERIM). The researchers found the patterns in Landsat MSS data of agricultural fields as a function of the life cycle of the crop. Essentially, as crops grow from seed to maturity, there is a net increase in near-infrared and decrease in red reflectance based on soil color

WEIGHTS FOR TASSELED CAP TRANSFORMATION OF LANDSAT MSS DATA

Component	Channel 1	Channel 2	Channel 3	Channel 4
Brightness	0.433	0.632	0.586	0.264
Greenness	-0.290	-0.562	0.600	0.491
Yellowness	-0.829	0.522	-0.039	0.194
"Non-such"	0.223	0.012	-0.543	0.810

Green Red NIR1 (vegetation) NIR2(anti-haze)

Tasseled Cap Transformation

Three new channels are created by applying coefficients to the input bands:

So each pixel is assigned a new DN in 3 new created channels.

TC1,2,3 (Landsat MSS) = a * MSS1 + b* MSS2 + c * MSS3 + d * MSS4

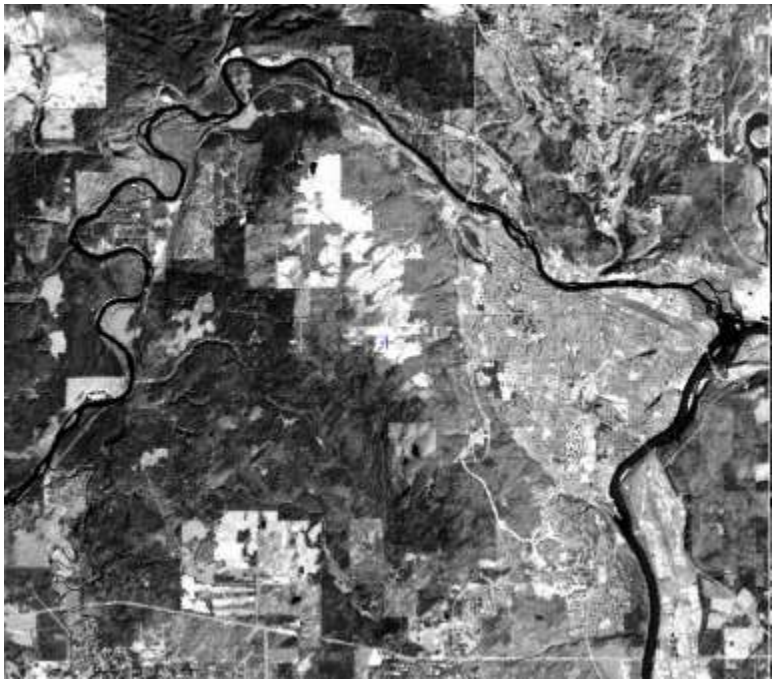
TC1,2,3 (Landsat TM) = e *TM1 + f*TM2 + g*TM3 + h*TM4 + j*TM5 + k*TM7

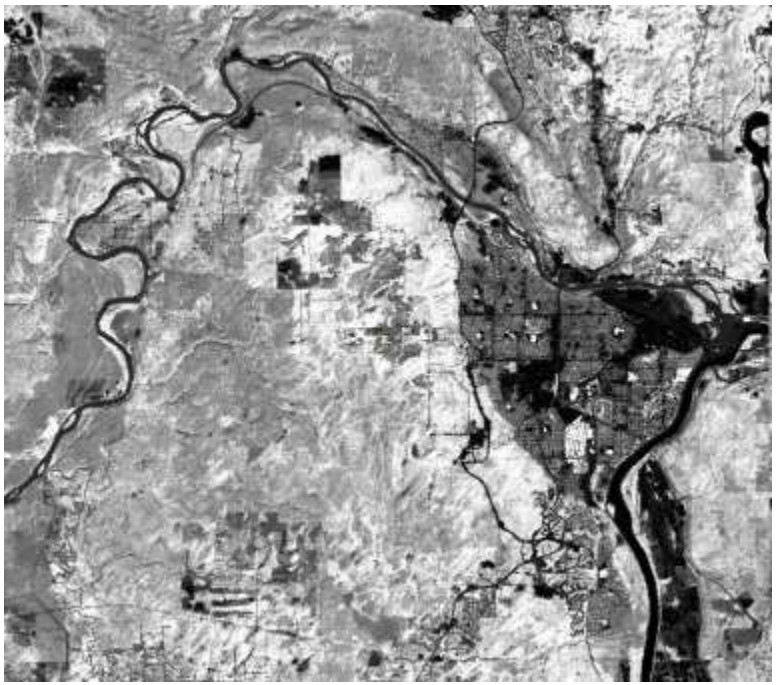
MSS data, the 4-band dataset created channels:

Brightness, Greenness and Yellowness

TM data, the 6-band (no thermal) creates:

Brightness, Greenness and Wetness





Brightness – measure of soil reflectance

Greenness – vegetation

Wetness – soil and canopy moisture

tasseled cap channels 1,2,3

Tasseled Cap Transformation

Landsat 5 TM coefficients for the Tasseled Cap

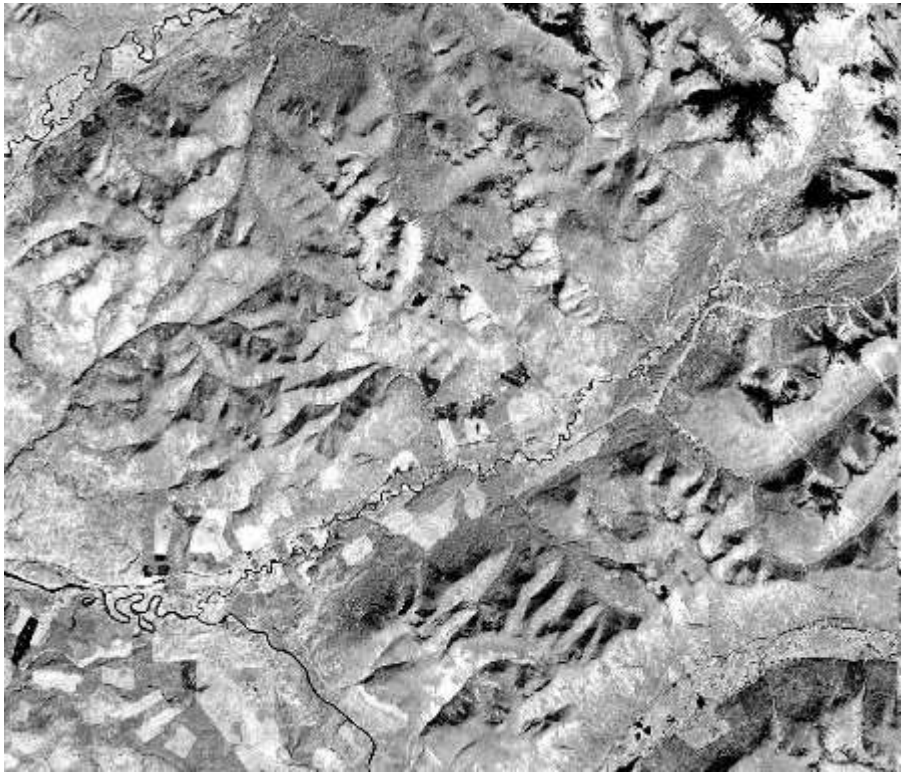
Band	Brightness	Greenness	Wetness
1	.3037	-.2848	.1509
2	.2793	-.2435	.1973
3	.4743	-.5436	.3279
4	.5585	.7243	.3406
5	.5082	.0840	-.7112
7	.1863	-.1800	-.4572
Character:	**Overall reflectance**	**NIR v Visible**	**MIR v NVIR**

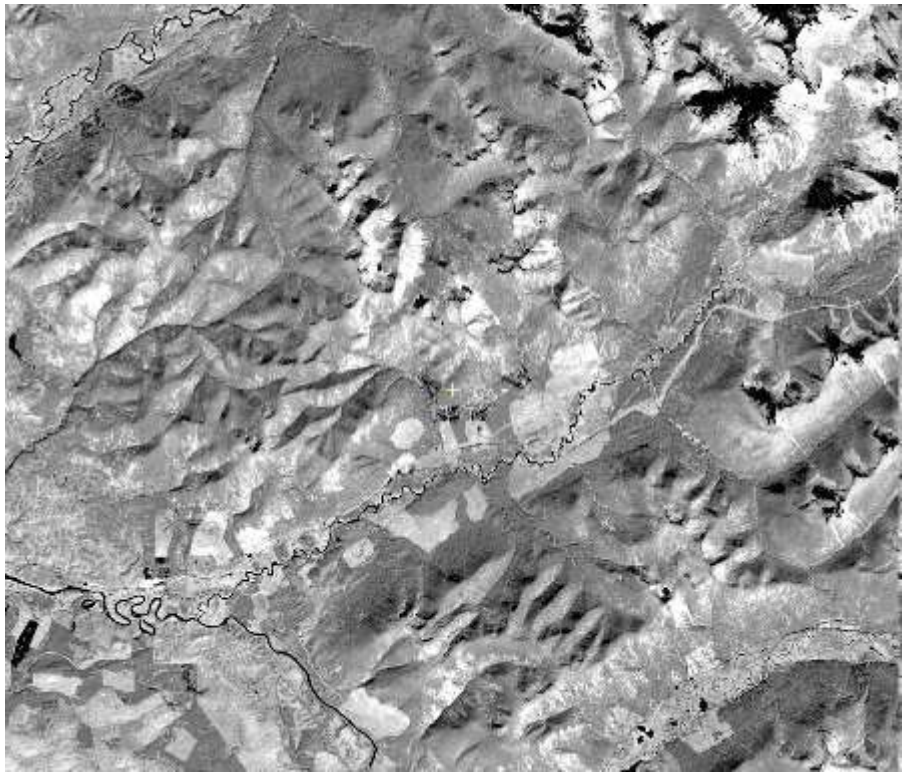
Rationale for using Tasseled Cap

- It reduces a multi band dataset (4-6) to 3 channels – Brightness, Greenness, Wetness – each might be useful
- The 3 channels could be used in classification
- The coefficients are universal for each sensor

NDVI v Tasseled Cap greenness

both contrast NIR versus visible reflectance





TCA Greenness is similar to NDVI, with subtle differences and used in habitat studies.

Figure :John Paczkowski MSc thesis – **remote sensing and grizzly bear habitat**

Landsat 5 TM data

WEIGHTS FOR TASSELED CAP TRANSFORMATION OF THEMATIC MAPPER DATA						
Component	**Channel 1**	**Channel 2**	**Channel 3**	**Channel 4**	**Channel 5**	**Channel 7**
Brightness	0.3037	0.2793	0.4343	0.5585	0.5082	0.1863
Greenness	-0.2848	-0.2435	-0.5436	0.7243	0.0840	-0.1800
Wetness	0.1509	0.1793	0.3299	0.3406	-0.7112	-0.4572

Landsat 8 OLI coefficients

	Coastal Band 1	*Blue Band 2*	*Green Band 3*	*Red Band 4*	*NIR Band 5*	*SWIR1 Band 6*	*SWIR2 Band 7*
Brightness	0	0.3029	0.2786	0.4733	0.5599	0.5080	0.1872
Greenness	0	-0.2941	-0.2430	-0.5424	0.7276	0.0713	-0.1608
Wetness	0	0.1511	0.1973	0.3283	0.3407	-0.7117	-0.4559

Why are they different at all ?

Sensors supported in Catalyst Focus Tasseled Cap algorithm:

Only Landsat MSS, TM and ETM+ until almost 2020

Deimos-1
DMC
Resourcesat-2 LISS-4
ALI
ALOS Avnir-2
CBERS-4 MUX
CBERS-4 WFI
Deimos-2
FASat Charlie
Formasat-2
Gaofen 1
Gaofen 2
GeoEye-1
Gokturk1
Ikonos-2
IRS-1A
IRS-2B
KazEOSat-2
SAC-C
KOMPSAT-2
KOMPSAT-3
OrbView-2
PeruSAT-1
Pleiades
QuickBird
RapidEye
SuperView-1
TripleSat
WorldView-2 to 4
ZY-3
ZY3-2
ASTER
CBERS-4 P10
IRS-1C / D
IRS-P6
Resourcesat-2 AWiFS
Resourcesat-2 LISS-3
Sentinel -2

Principal Components Analysis (PCA)
initially known as (Harold) 'Hotelling'

Large datasets are increasingly common and often difficult to interpret. Principal component analysis (PCA) is a technique for reducing the dimensionality of such datasets, increasing interpretability but minimizing information loss, by creating new uncorrelated variables that successively maximize variance.

Finding such new variables, the principal components, reduces to solving an eigenvalue/eigenvector problem, and the new variables are defined by the dataset at hand, **not *a priori***, hence making PCA an adaptive data analysis technique.

Principal component analysis: a review and recent developments.
Jolliffe IT, Cadima J. 2016
Phil. Trans. R. Soc. A 374: 20150202.
http://dx.doi.org/10.1098/rsta.2015.0202

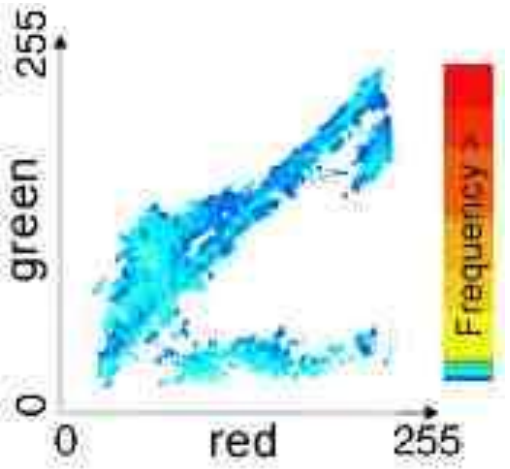
PC1 = what is common between images (no change)

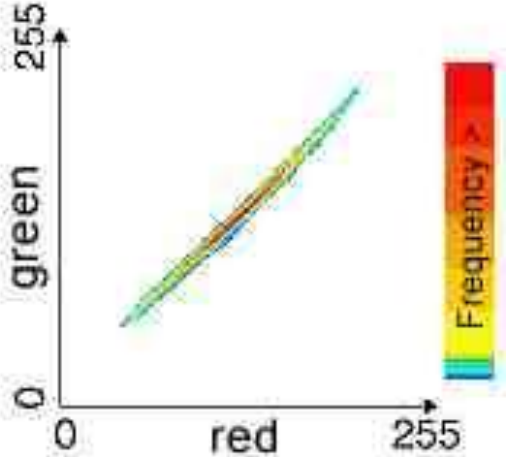
PC2 = what is different – between most different sets

PC3 ....-> = what is another difference … and so on …

Principal Components Analysis (PCA)

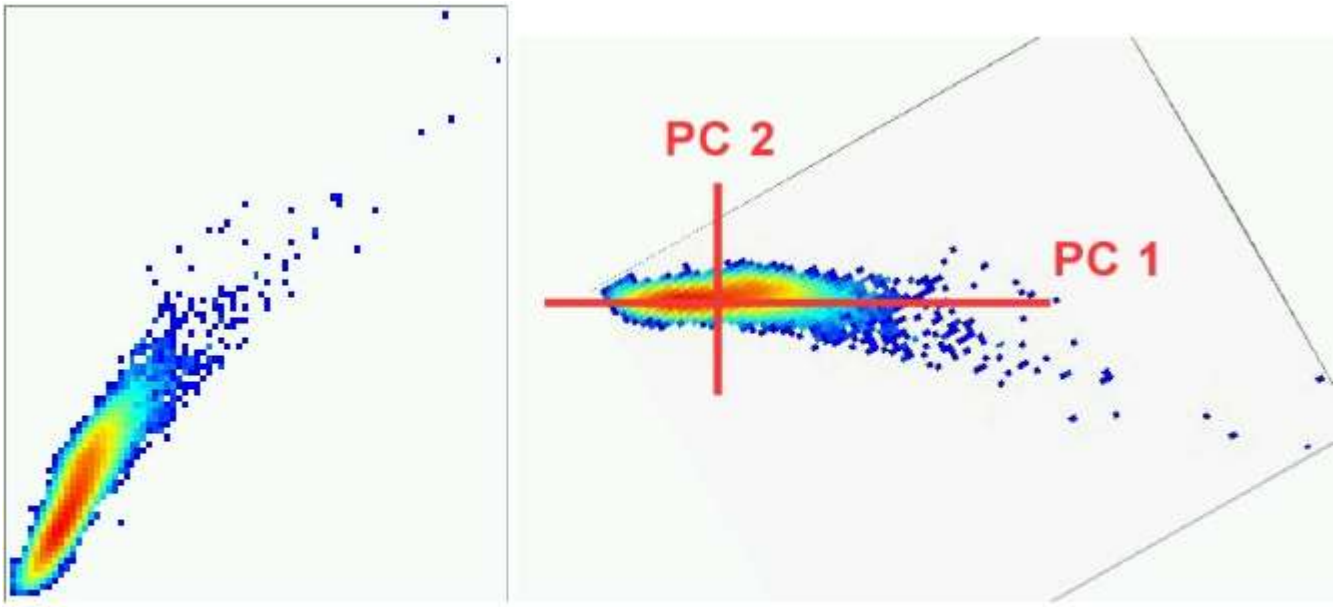
PCA is a mathematical transformation that converts original data into new data channels that are uncorrelated and minimise data redundancy.
Like TCA, it can also: reduce shadows and spectral correlation between bands





http://eoedu.belspo.be/en/guide/compprin.asp

http://geology.wlu.edu/harbor/geol260/lecture_notes/Notes_rs_PC.html



Now ! imagine this in 3d, or in 7 dimensions, which includes all of the bands.

The bands can be reduced to their respective 'components', by an 'axial rotation'

The main axis through the points is a 'component'; if all points were on it, correlation=1, the first component (PC1) would 'explain' all the variation.

The 2nd component (PC2) is normal to PC1, uncorrelated and hence two bands are converted to two components, but most variation is explained by the first (the 2nd is always smaller)

Principal Components Analysis (PCA)

The new channels are defined by eigenvectors / eigenvalues.

In the 'matrix':

Eigenvectors: define the contribution of each band (loadings)

Eigenvalues: 'explain' the % variance of each PCA channel

PC1 and PC2 often explain 95-99% and PC3 most of the rest

PC1= what is explained in both bands (images)

PC2= what is different between them (similar to a band ratio)

PCA channels (PG image)

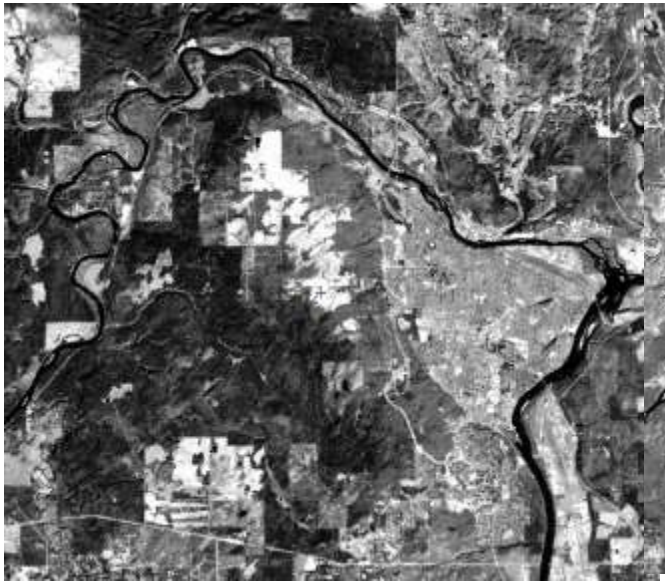
Eigenvectors of covariance matrix (arranged by rows):

	TM1	2	3	4	5	6	7
PC1	0.22	0.15	0.29	0.16	0.75	0.33	0.40
PC2	-0.28	-0.14	-0.29	**0.82**	0.23	-0.25	-0.16
PC3	**0.51**	**0.31**	**0.43**	**0.49**	-0.46	-0.05	-0.00
PC4	-0.09	-0.09	-0.19	0.19	-0.23	**0.91**	-0.18
PC5	0.31	0.13	0.05	-0.12	**0.35**	-0.00	-0.86
PC6	**0.69**	-0.16	-0.68	-0.01	0.01	-0.04	0.19
PC7	-0.19	**0.90**	-0.39	-0.04	0.00	0.00	0.06

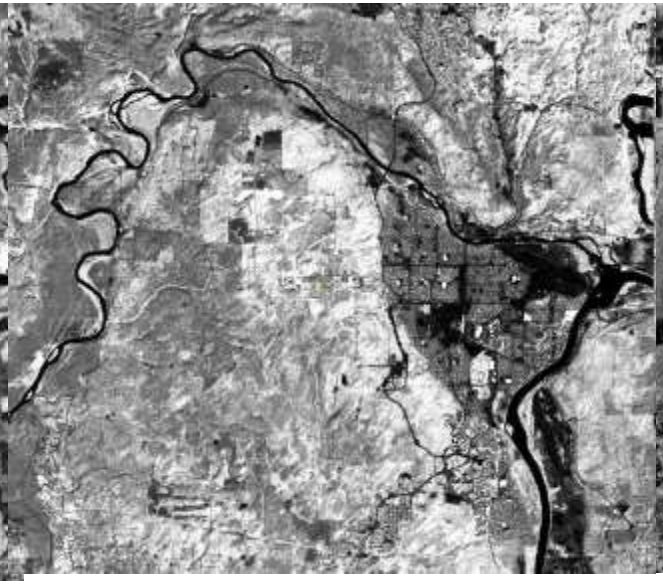
Component

71% Brightness
21% Greenness
3.8% Swirness / Wetness
2.3% Impact of TM6
1.6% Band 5 v 7 (MIR)
0.2% Band 1 v 3 (B v R)
0.1% Band 2 v 3 (Yellowness)

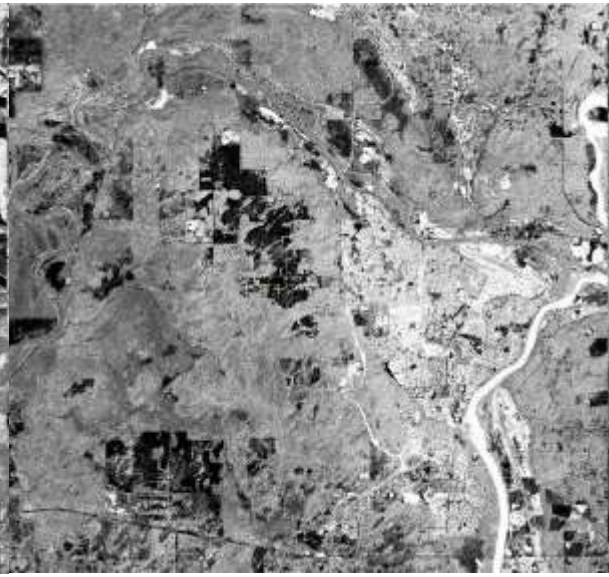
PC1: Brightness,



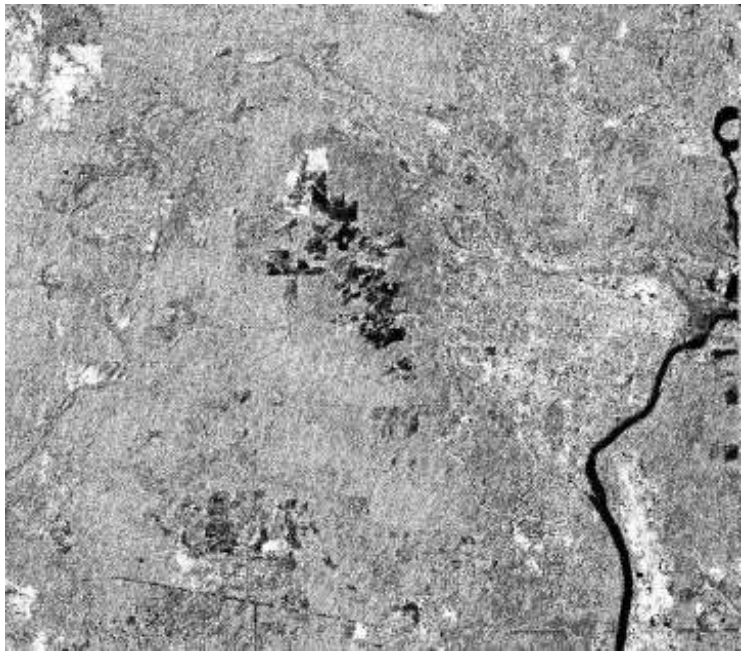
PC2: Greenness,

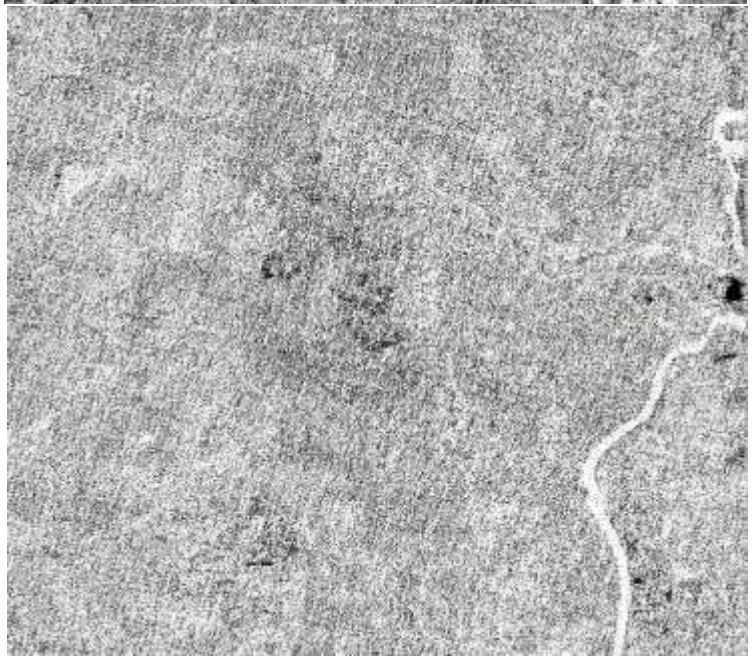


PC3: Swirness / Wetness



PC components PC4: TM6, PC5: TM5/7, PC6: TM1/3, PC7: TM2/3





Differences with Tasseled Cap (TCA) :

1. PCA transformation is scene specific, while TCA coefficients are 'global'

2. PCA generates as many components as there are input **channels**
- TCA creates only three new transformed **channels**

e.g. for Landsat TM, there could be 7 new component channels

Thus PCA can also be used to combine and analyse extensive multi-temporal datasets (time series analysis) or 'hyperspectral' data

PCA – Time series analysis

36 monthly AVHRR NDVI images (1 km) – over 3 years

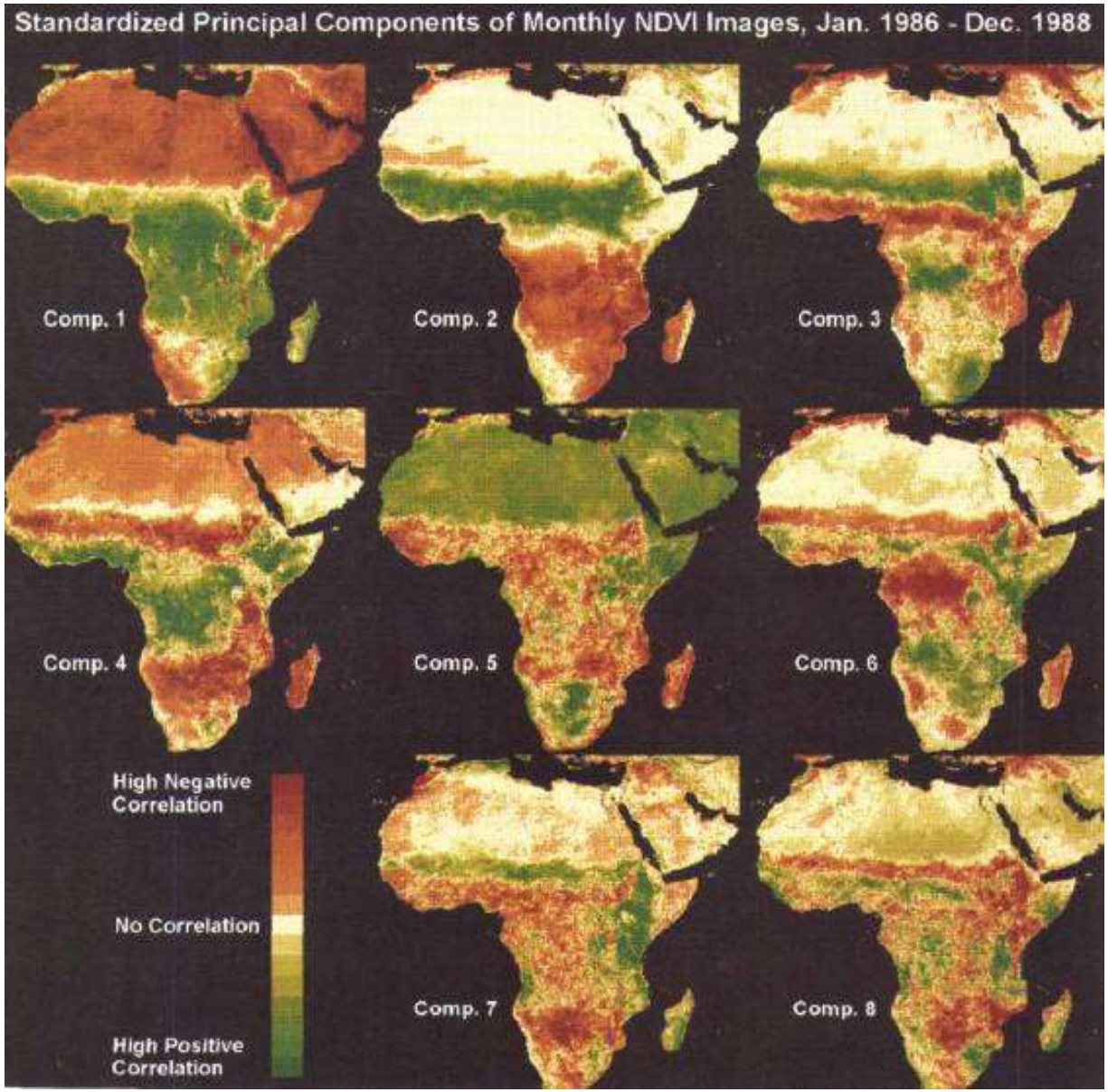
PC1: average NDVI

PC2: seasonal change

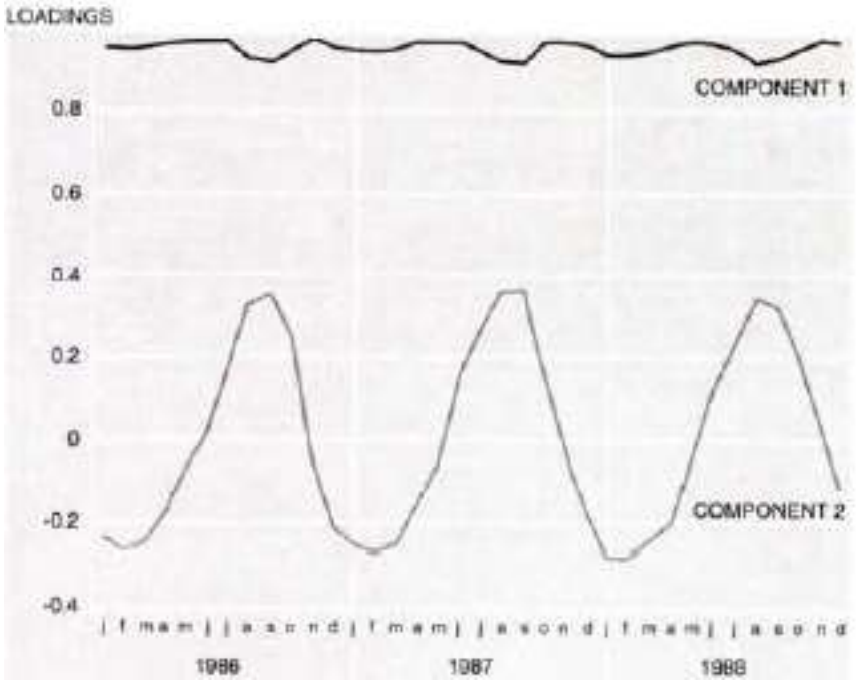
PC3: May vs Nov

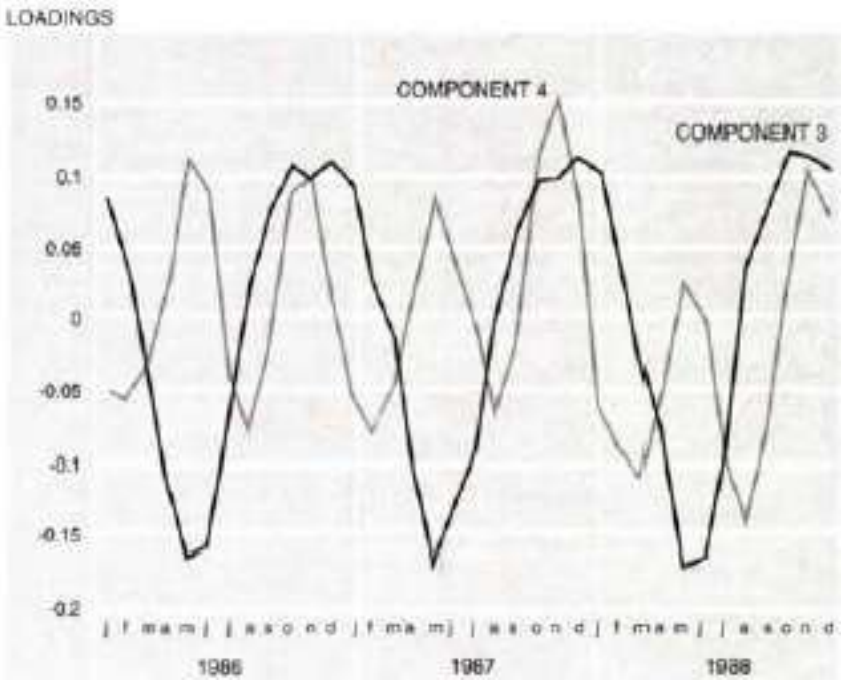
PC4: Oct /April v Feb/Aug

Eastman and Fulk, 1993, "Long sequence time series evaluation using standardized principal components" Photogrammetric Engineering and Remote Sensing, 59, 8, (August) 1307-1312.



Loadings (eigenvectors)
(= correlation with original images)

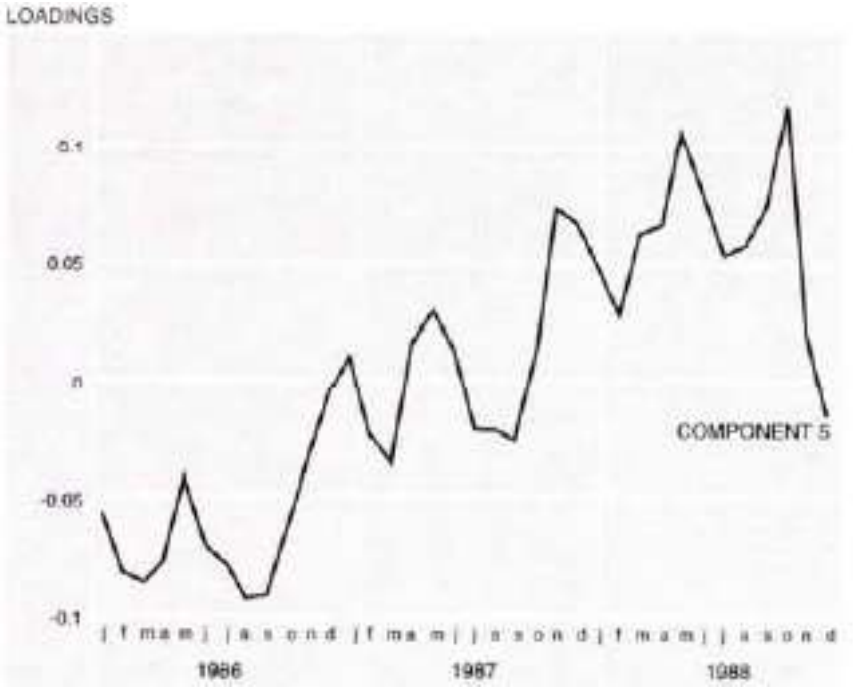


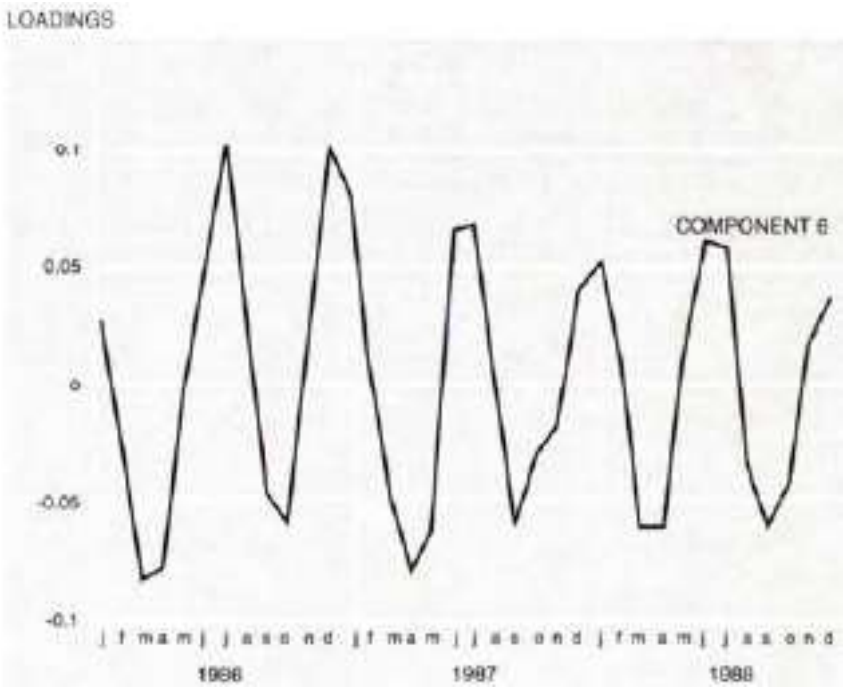


PC1 and PC2
Overall NDVI brightness
summer-winter difference

PC3 and PC4
May/November
Oct /April v Feb/Aug

Sensor changes due to orbit time drift – later time of day





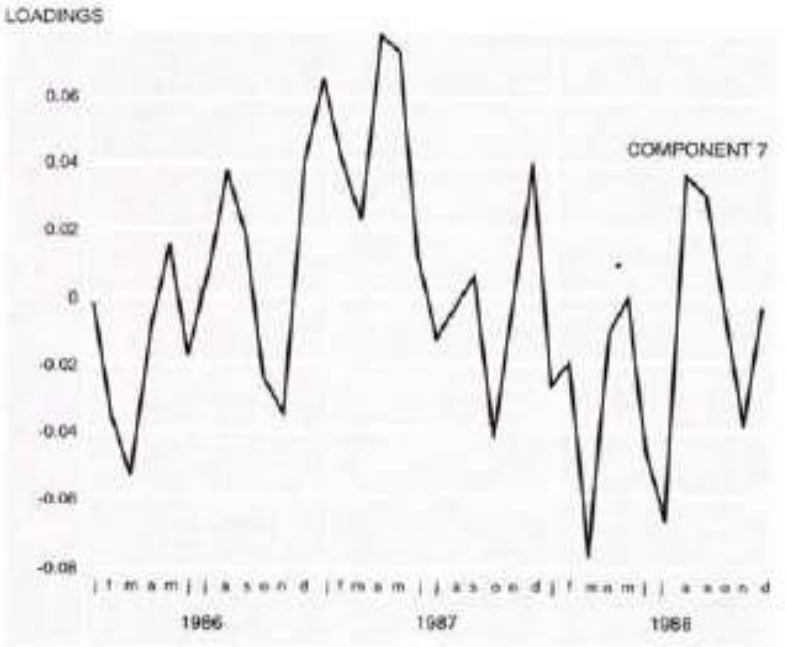
PC5

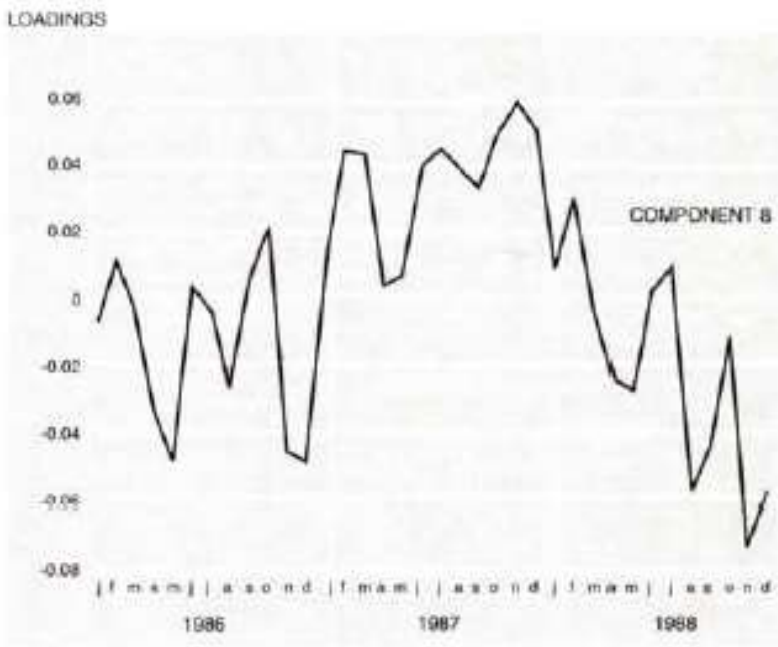
Apparent increase in NDVI from sensor drift
(Red affected more than NIR)

PC6

decreasing amplitude of NDVI effect in forests

El Nino effects





1. Loadings (Y-axis) of the original monthly images (X-axis) on the first eight standardized principal components. Loadings ually be thought of as the correlation between the original images and the derived components.

PC7

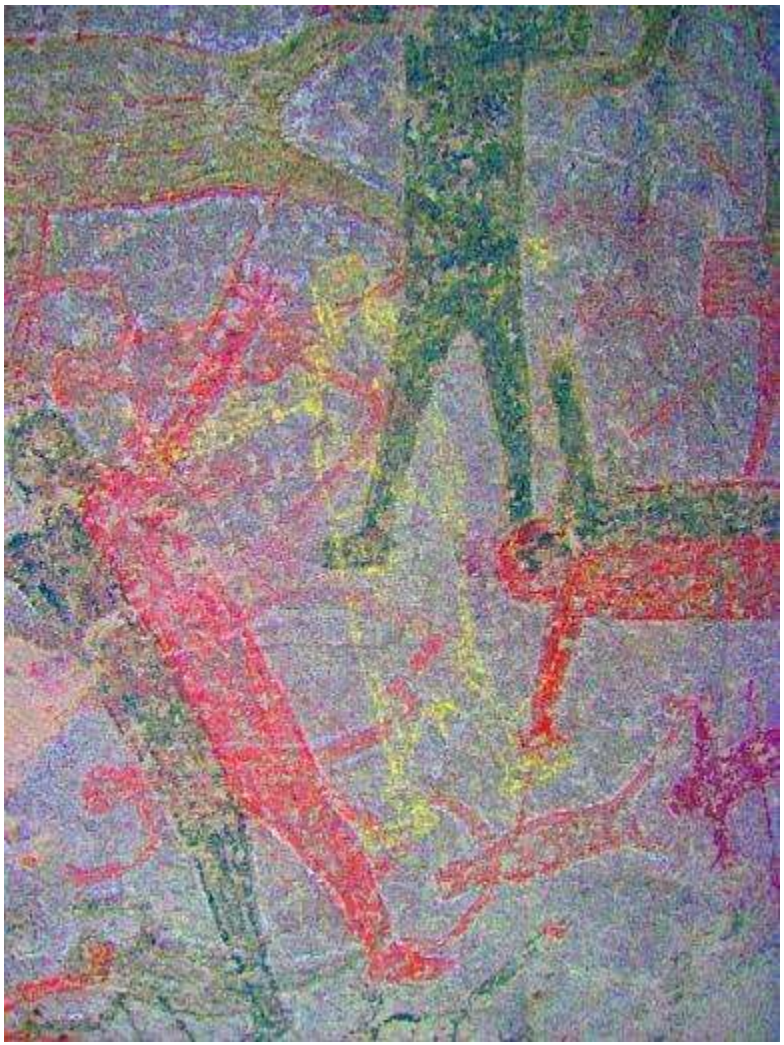
PC8

There could be up to 36 components: the rest will show local differences or noise

Decorrelation Stretch: Remote sensing technique to enhance images

- **Based on Principal Components Analysis (PCA) – PCI algorithm: DECORR**

- **used to Enhance Rock Art Images** By Jon Harman, Ph.D.



Hyperspectral remote sensing ('Image spectroscopy')

Multispectral systems contain ~5-10 bands (70-400 nm wide = 0.07-0.40 µm)
e.g. Landsat TM (below)

Superspectral = 15-50 bands e.g. MODIS

Hyperspectral consists of 100- 200+ channels from 0.38 - 2.5µm (5-10nm each)
Bands are contiguous and high spectral resolution

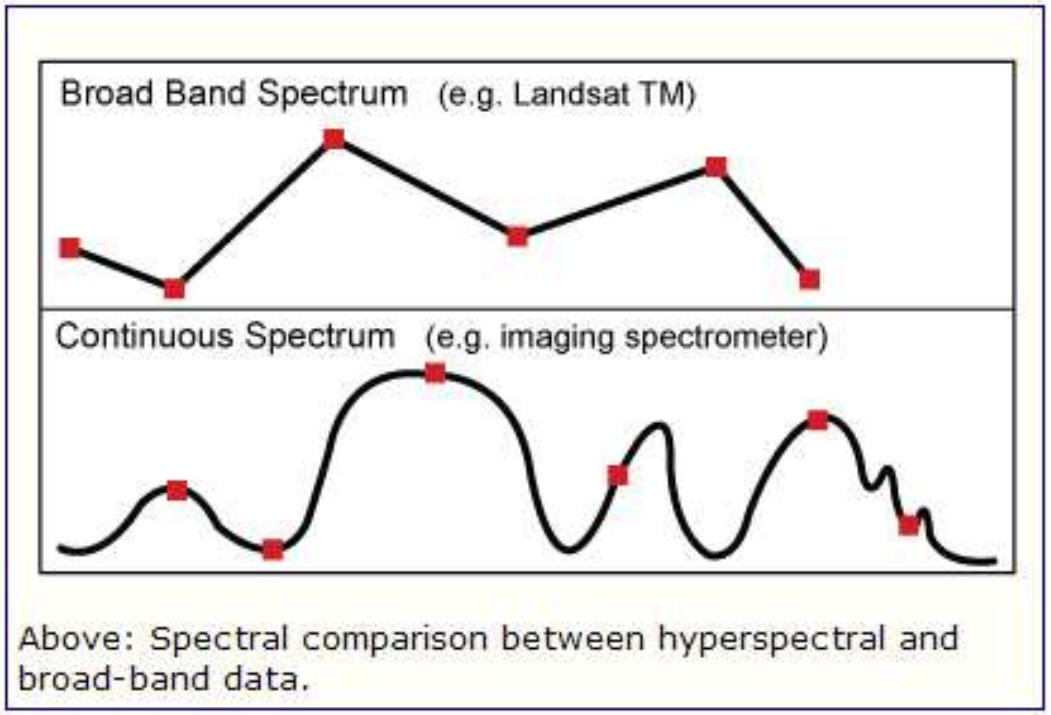
e.g. For comparison: Landsat TM:

Landsat 5 (TM sensor)	Wavelength (micrometers)	Spectral resolution (nm)
Band 1	0.45 - 0.52	70
Band 2	0.52 - 0.60	80
Band 3	0.63 - 0.69	60
Band 4	0.76 - 0.90	140
Band 5	1.55 - 1.75	200
Band 6	10.40 - 12.50	2100
Band 7	2.08 - 2.35	270

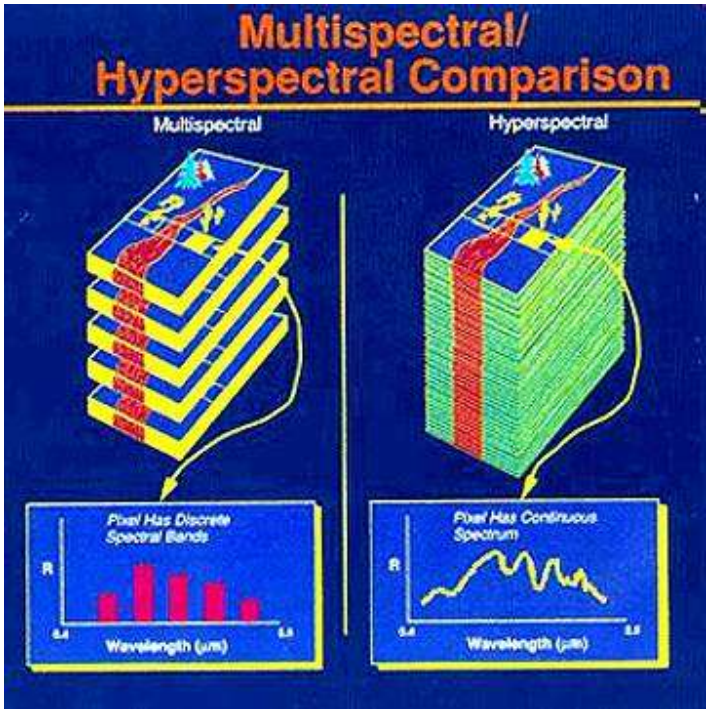
Some airborne hyperspectral systems

Sensor	Wavelength (nm)	Band width (nm)	# bands
AVIRIS	400-2500	10	224
TRWIS III	367-2328	5.9	335
HYDICE	400-2400	10	210
CASI (1500)	400- 900	1.8	288
OKSI AVS	400-1000	10	61
ESSI Probe-1	400-2450	15	128

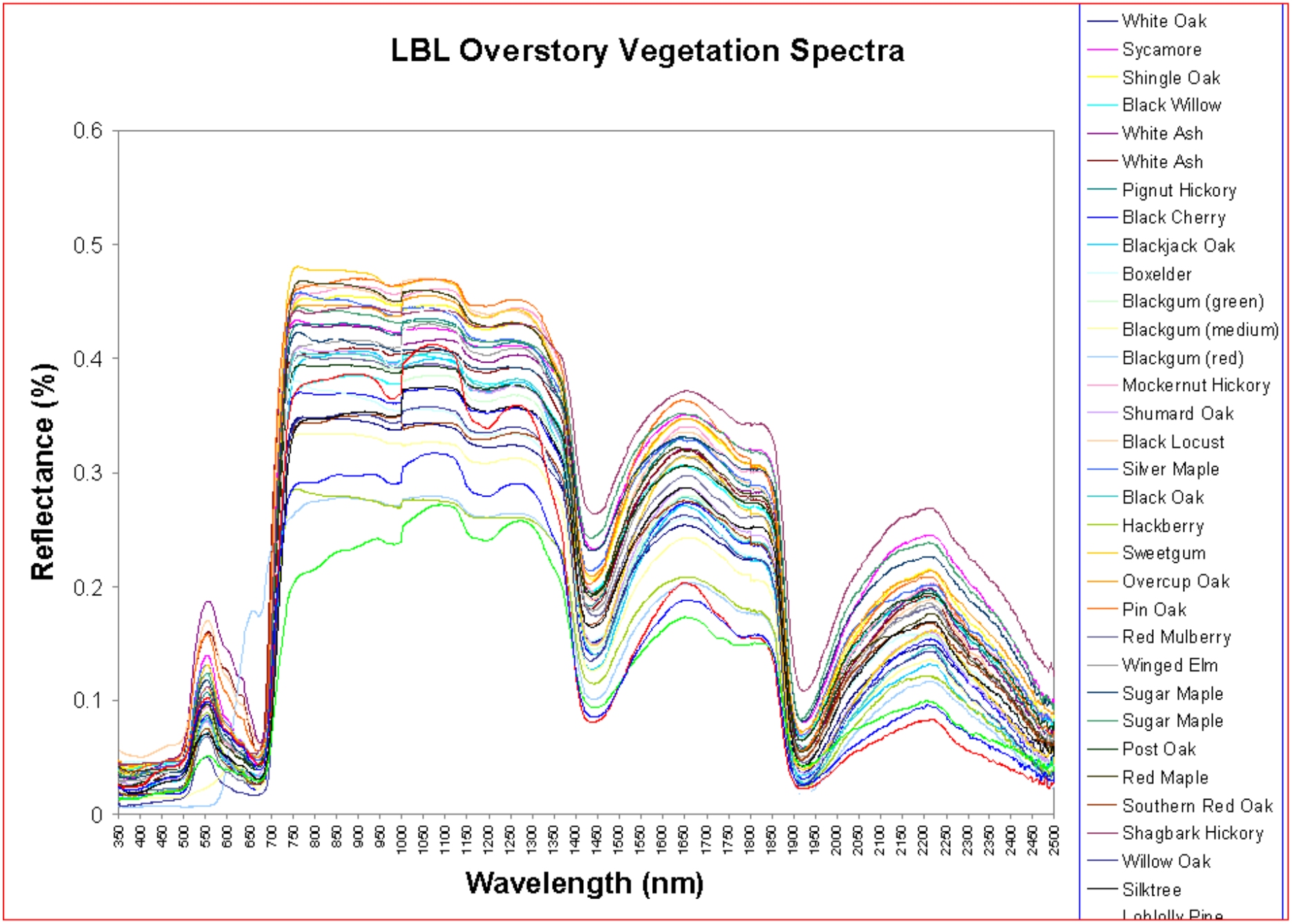
Spectral signatures: Landsat TM v hyperspectral



Above: Spectral comparison between hyperspectral and broad-band data.



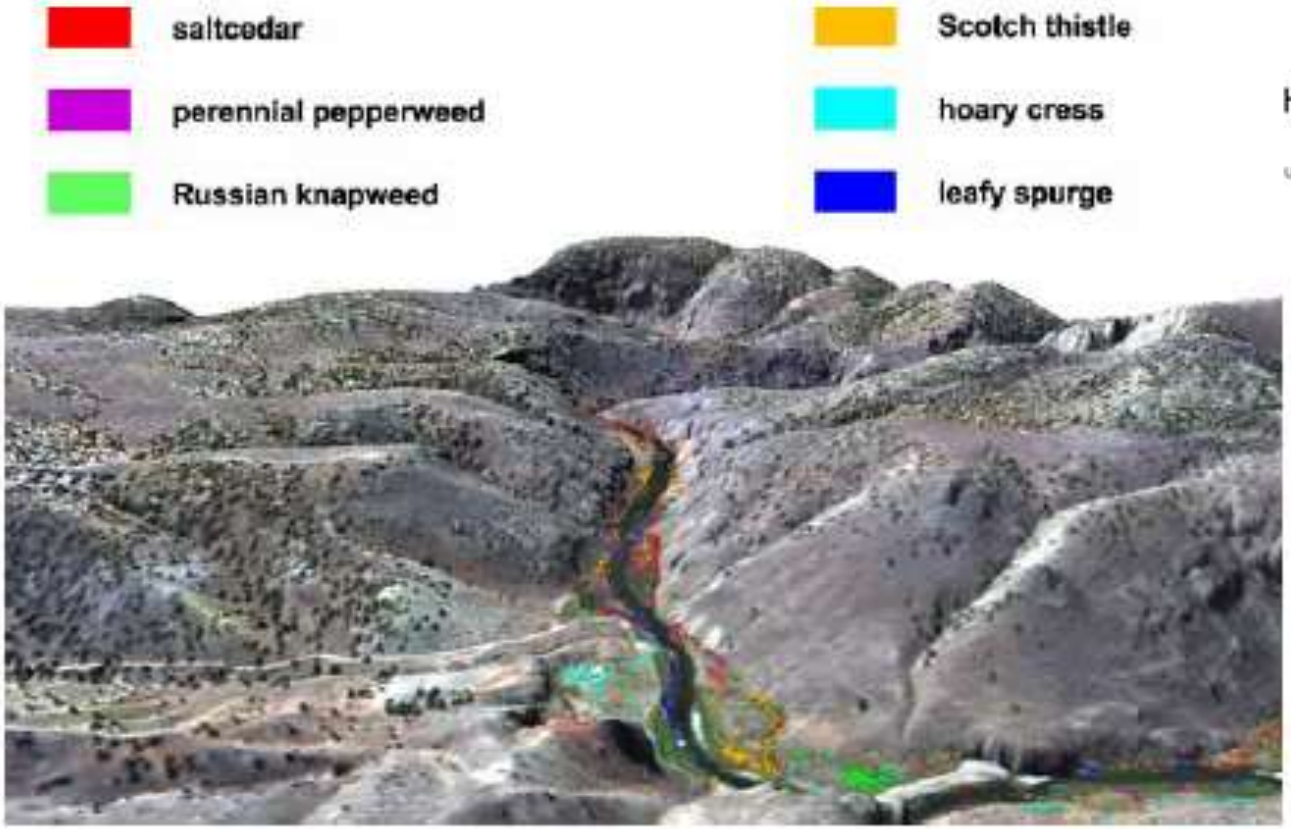
http://www.ccrs.nrcan.gc.ca/hyperspectral/isst_e.php



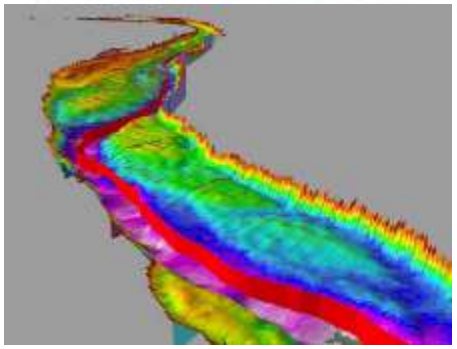
http://www.murraystate.edu/qacd/cos/marc/projects/nasa98/veg_library/lblspec.gif

Quantifying structural physical habitat attributes using LIDAR and hyperspectral imagery

Environ Monit Assess (2009) 159:63–83

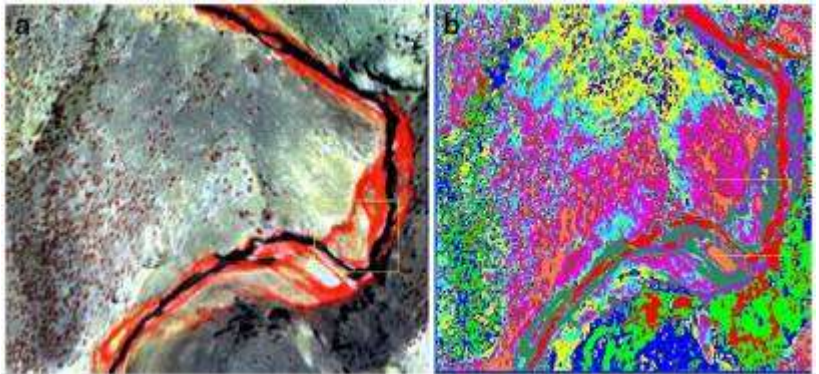


Hyperspectral ✶ Lidar
Research Group
UNIVERSITY OF VICTORIA



<- LiDAR DEM

IR image and 10 class -> ISODATA classification



CASI (Compact Airborne Spectrographic Imager) - ITRES, Calgary

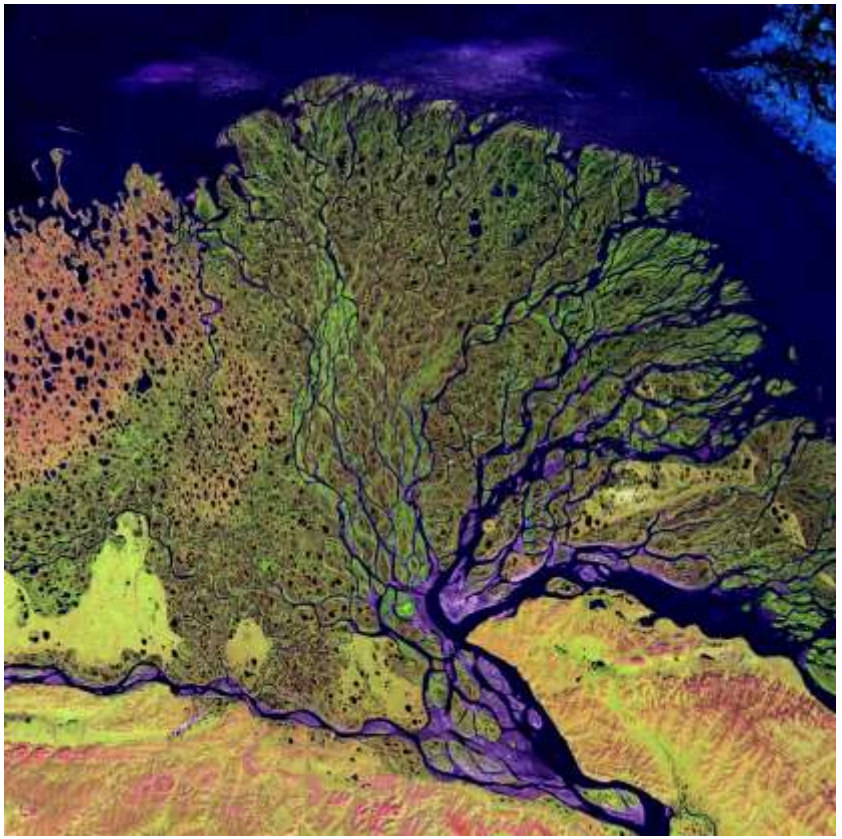
www.itres.com

1989 CASI 1	400-900	0.5-10m pixels, 12 bit data (0-4095)
2002 CASI 2, 3	400- 1050	14 bit data (0-16383)
SASI-600	950-2450	100 bands x 15nm
MASI-600	3-5 µm	64 bands 1m
TASI-600	8-11.5 µm	32 bands
TABI -1800	8-12 µm	160 bands 320 pixels x 3metre (12 bit data)

MASI-600 flight line, 1m resolution.

Displayed 3 bands:
r: 3571 nm
g: 3952nm
b: 4778nm

SOME APPLICATIONS:



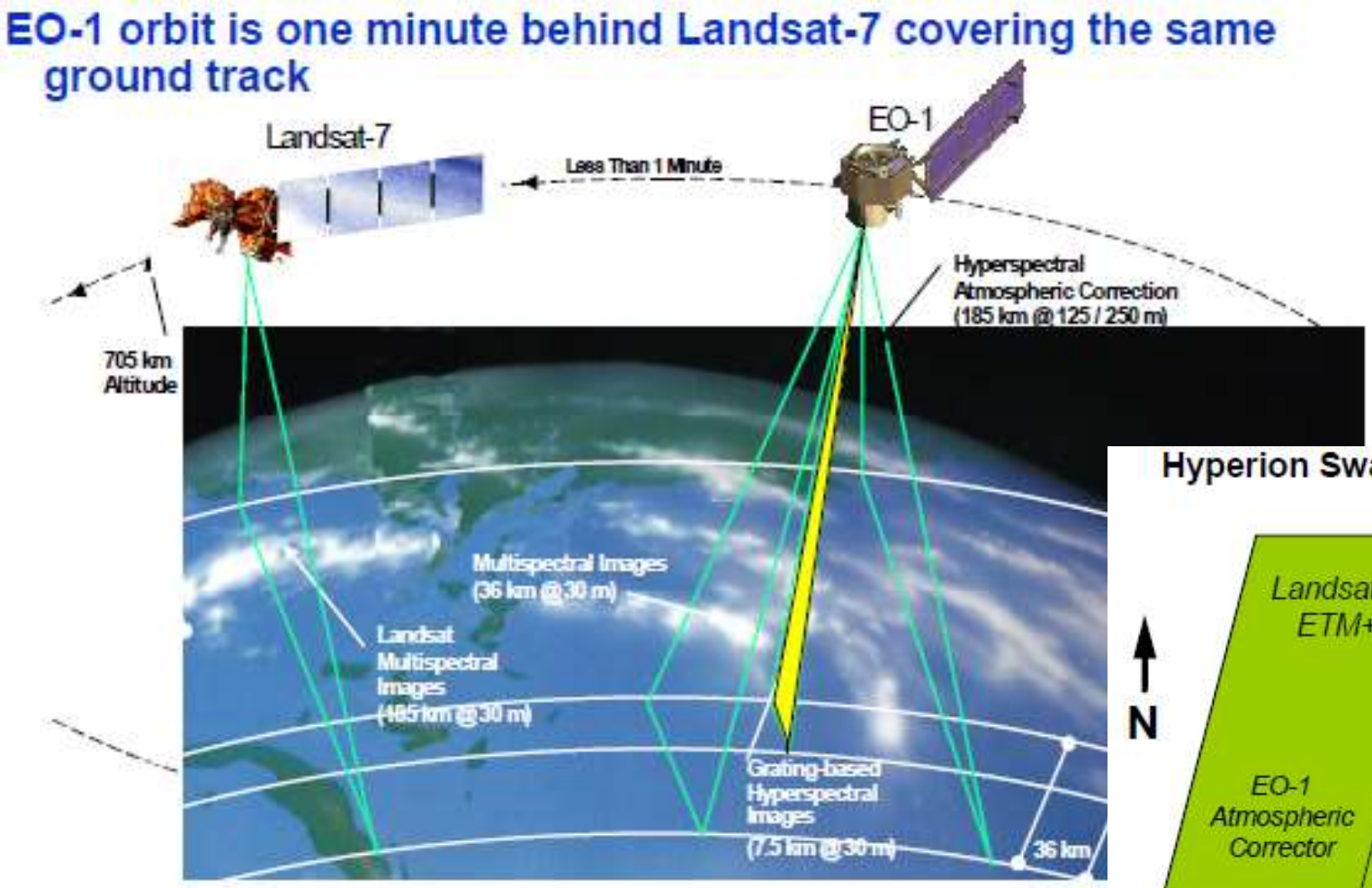
- wetland /coastal vegetation
- mineral composition
- agricultural crops
- forest structure
- soil types
- There is a clear link with PCA and so many bands:

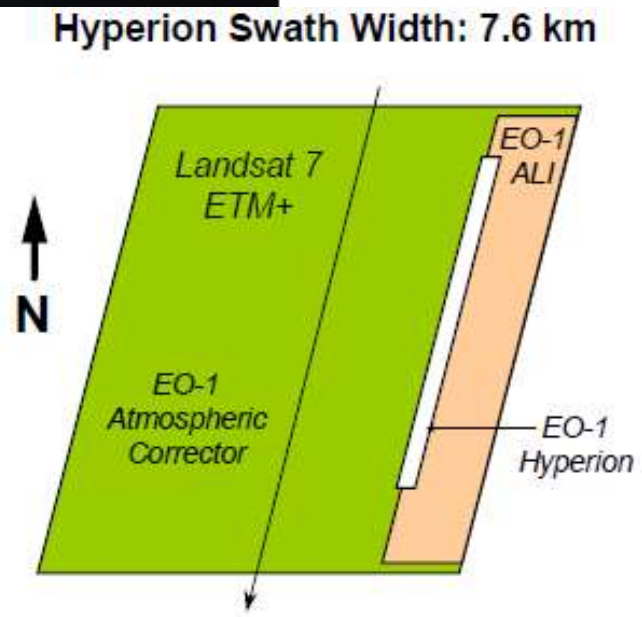
https://towardsdatascience.com/pca-on-hyperspectral-data-99c9c5178385

As many component channels as there are input bands …..

Satellite borne hyperspectral systems

Hyperion: launched on Earth Observing 1 (EO-1), Dec 2000; 50km behind Landsat7;





http://gers.uprm.edu/geol4048/pdfs/14_**hyperspectral**.pdf

Venice by CHRIS

(Compact High Resolution Imaging Spectrometer)

on PROBA (2001)

CHRIS provides 19 bands in the VNIR range (400 - 1050 nm) at 17 m. Each nominal image forms a square of 13 km x 13 km.

CHRIS can be reconfigured to provide a spatial resolution of 34 m and up to 150 channels.

Spaceborne Hyperspectral Applicative Land and Ocean Mission (SHALOM)

… is a joint mission by the Israeli Space Agency and Italian Space Agency to develop two commercial hyperspectral satellites, with planned launch in 2025

Ilan Ramon - the first Israeli astronaut

Final word: Does this help understand PCA ? ('non-technically')

Face Recognition Using Principal Component Analysis





Components

1: Human-ness (average of all)

2: Gender (/ skin colour) ? Male v female

3: Hair (colour / lack of) ? (related to gender except Justin)

4: Facial hair ? (Me and Don)

5: Mouth – Smile – Teeth – smirk ?

6-7: Age, Ears, Eyes, Nose … ?


Imagine we have a set of scanned, registered faces, each like a band and we apply PCA to the collection.