Dirty REMOTE SENSING : OBIA

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Web for the Week:
http://electronics.howstuffworks.com/gps.htm

http://www.cstars.ucdavis.edu/classes/ers186-w03/lecture17/lecture17.ppt

From Pixels to Objects

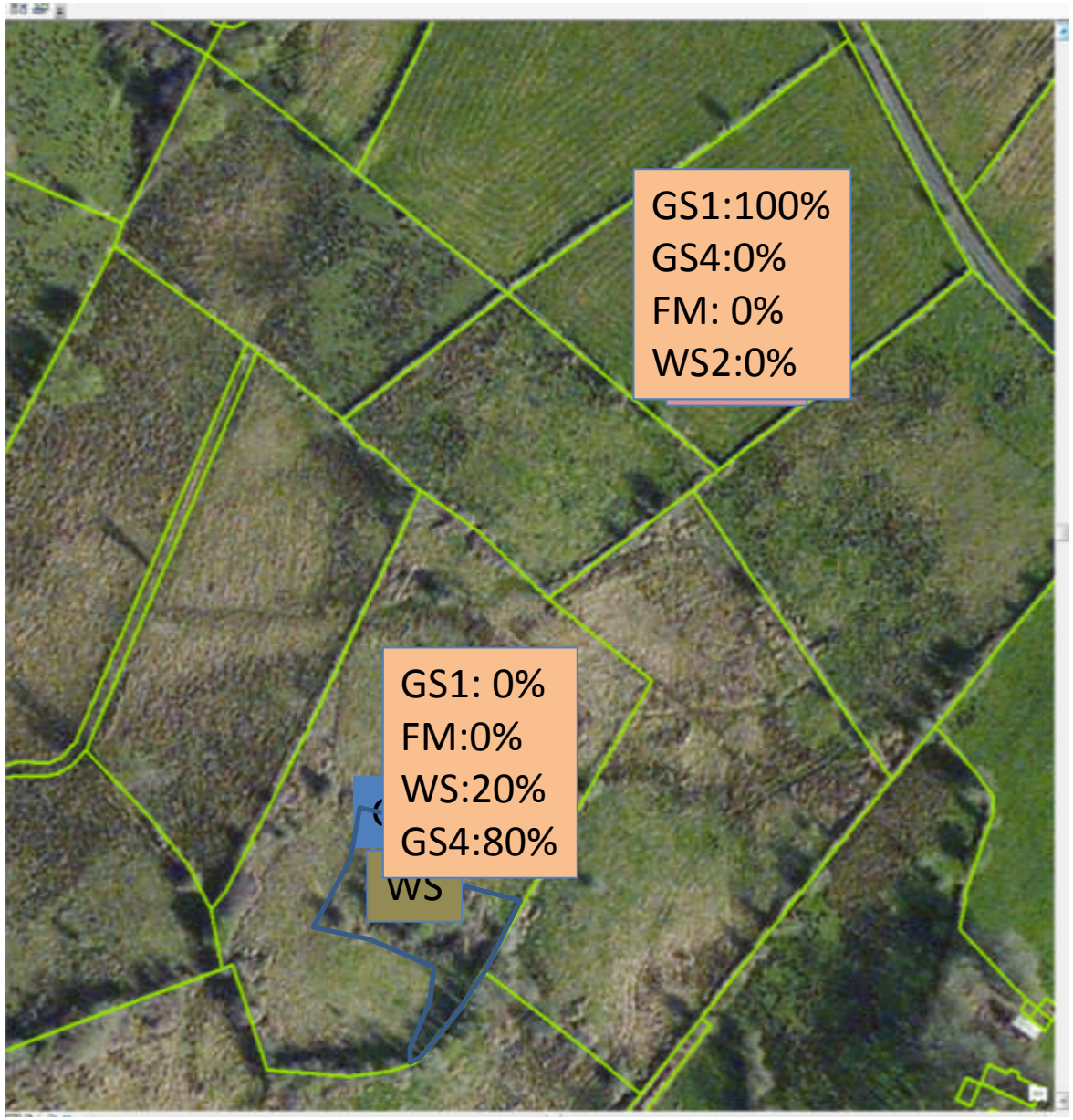
Previously we have looked at classification based only on the spectral characteristics of pixels one by one. But the information in an image isn't encoded in pixels but objects- things we recognise.

Objects are things on the Ground

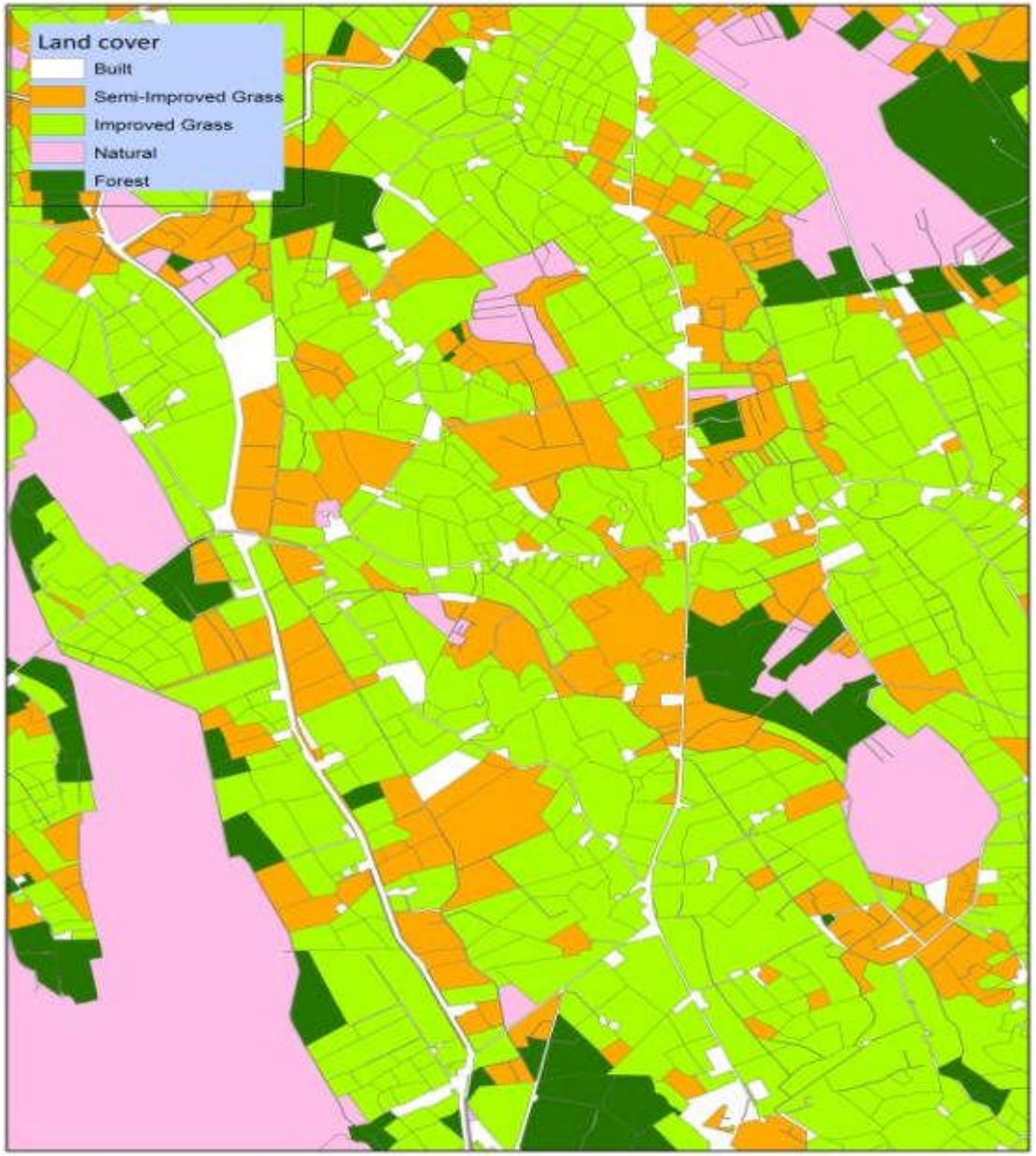
- Object Orientated Classifcation attempts to bring to gether many of the aspects of image interpreatation that we looked at early in the course on manual interpretation of imagery- like shadow, texture, context etc
- But do so in an automated fashion so the computer can create the outptut.

Objects

- We can have *a-priori* defined objects – cadastral maps for example (Prime 2 in the Irish context)
- Or we can create objects from the image using segmentation



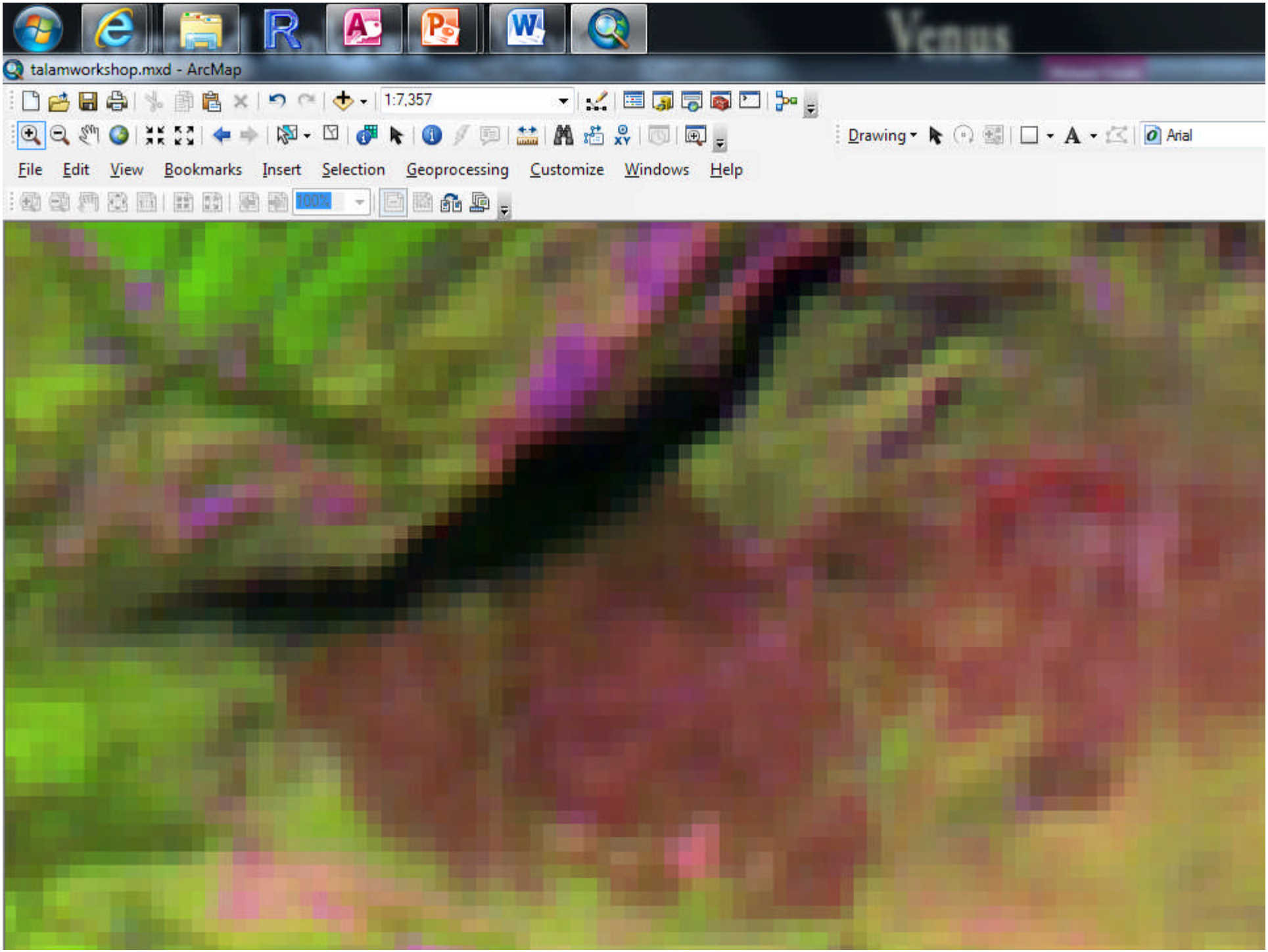
Scenario D


Land cover
Built
Semi-Improved Grass
Improved Grass
Natural
Forest

Unclosed areas

- What does landcover mean in these areas?
- How best to record extent and change?

- Classifications haven't been finalised- but will be guided by Helm and Eagle Internationally, Fossit locally and at all times with practicallity in mind.


talamworkshop.mxd - ArcMap
1:7,357
Drawing
Arial
File Edit View Bookmarks Insert Selection Geoprocessing Customize Windows Help
100%

Segmentation

- Essentially the segmentation algorithm examines how like its neighbours a pixel is- if pixels are alike they are grouped into objects.
- We can use colour of texture or the shape of the object to help us segment an image- most popular software for soing this is e-cognition

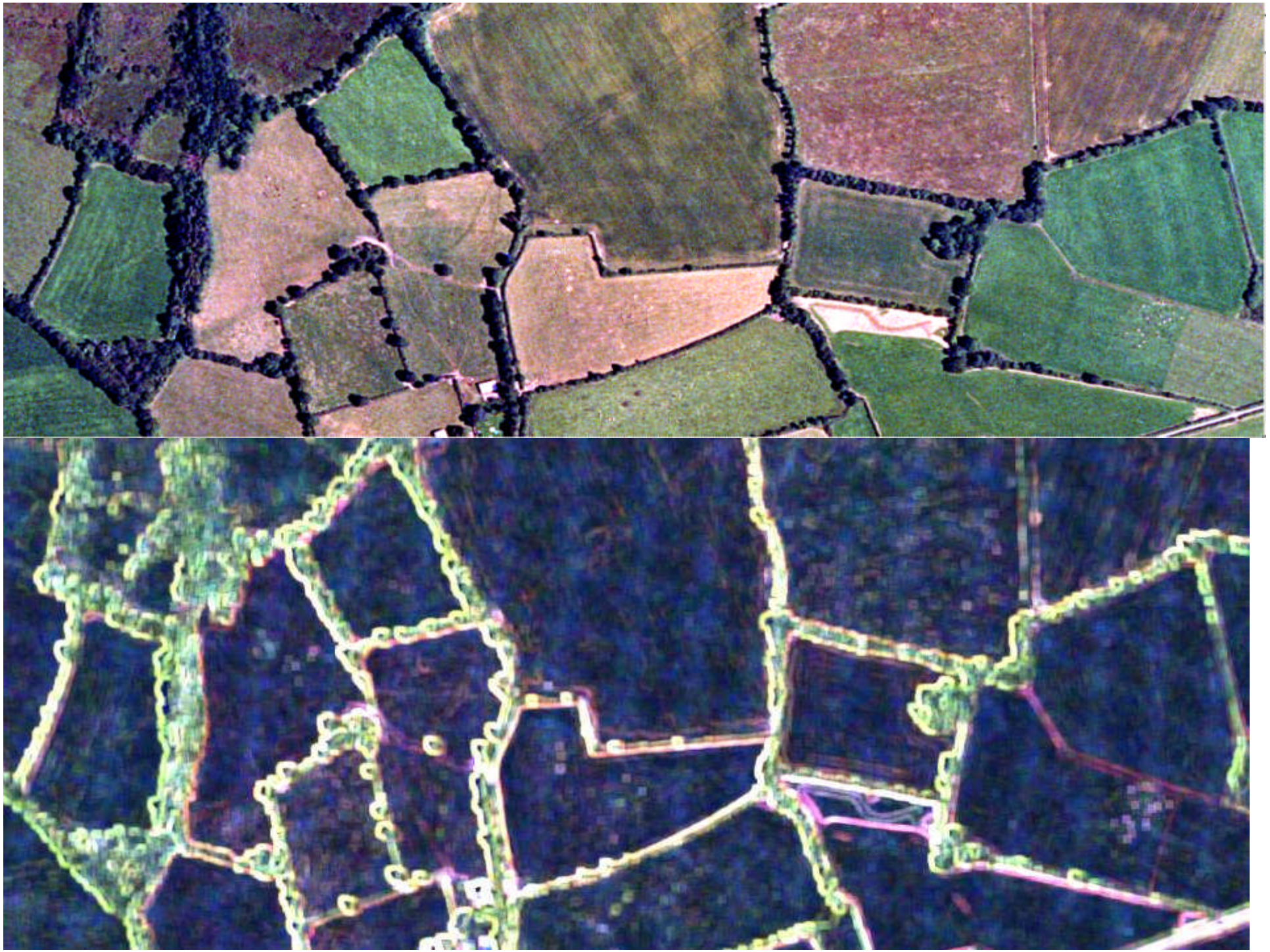
- Its very simalr to the human interpreation approach of mapping “photomorphic regions” and has been developed out of *machine vision* reserach

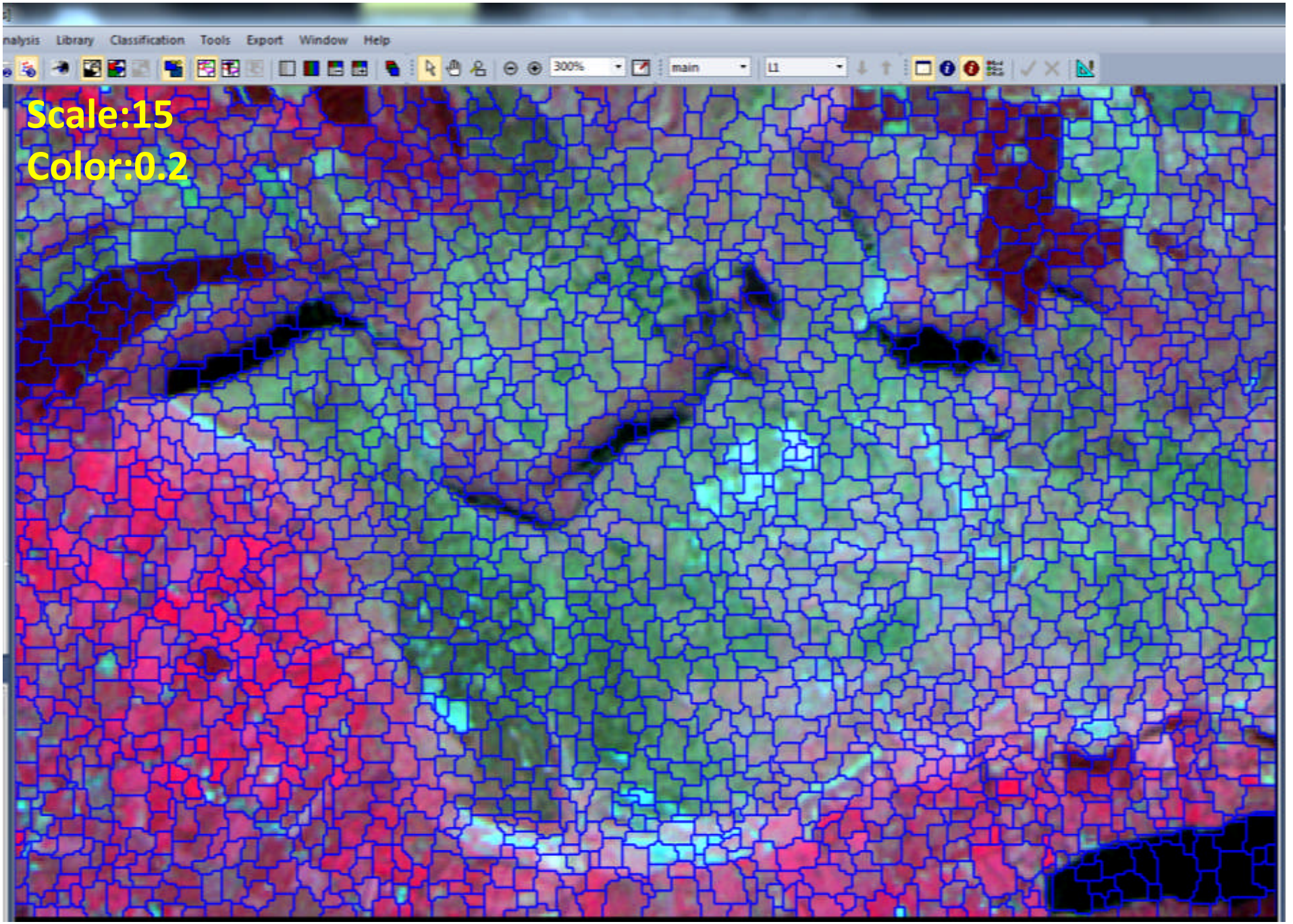
Texture

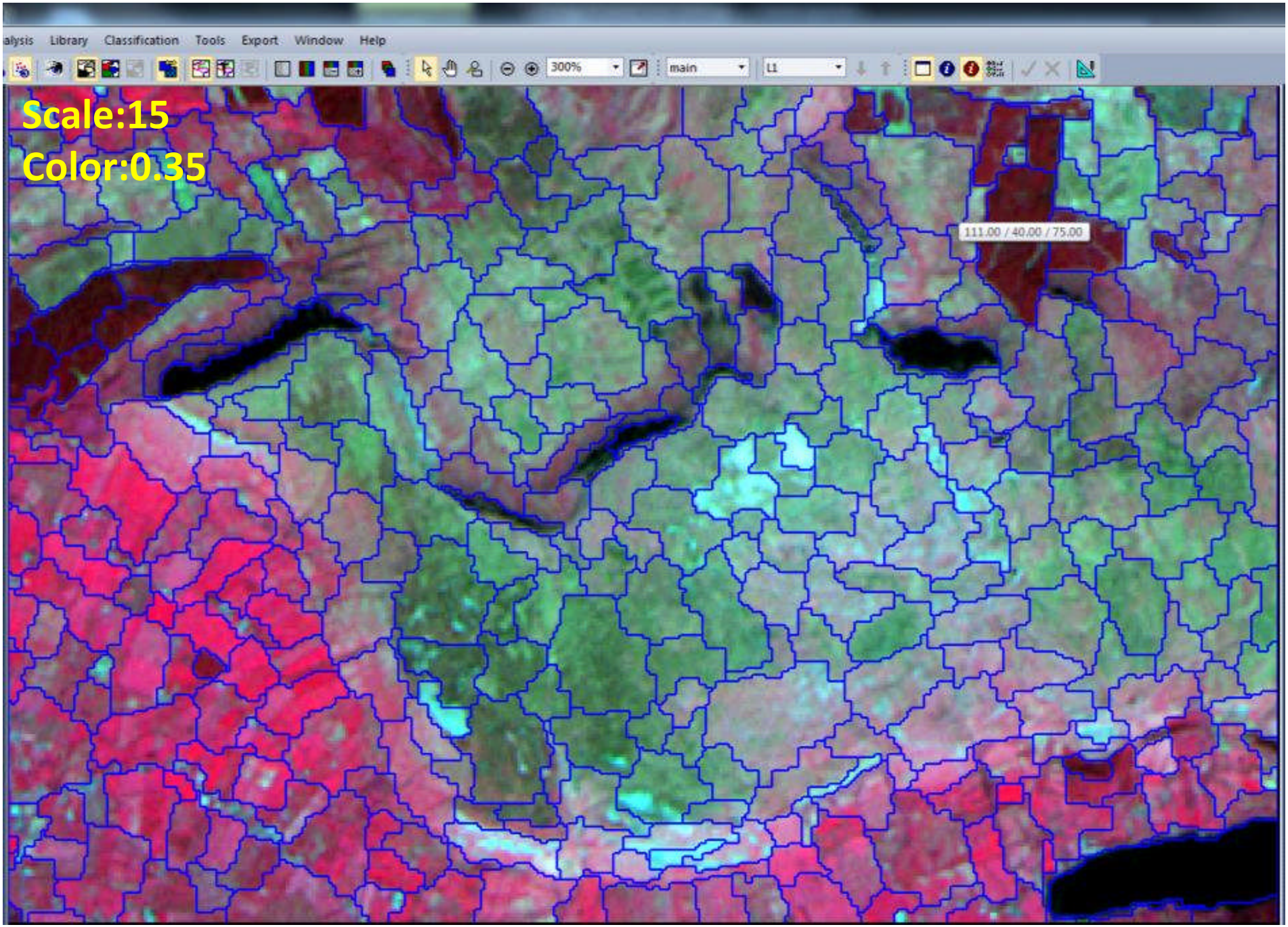
- Is a formal measurement of variation in tone. It’s a statistical measure based on a fixed sample known as a kernel
- In its simplest form it could be that every pixel is replaced with a value represents the standard deviation of the pixels around it

These segments become objects

- WE can then xclassify the object suing any of the classifcation we have looked at
- Unsupervised
- Supervised
- Rule based or descsion tree
- We can also include non-spectral data: eg the size of the object or its shape, the variation of pixels within an object (texture)




nalysis Library Classification Tools Export Window Help
300%
main
L1
Scale:15
Color:0.2


alysis Library Classification Tools Export Window Help
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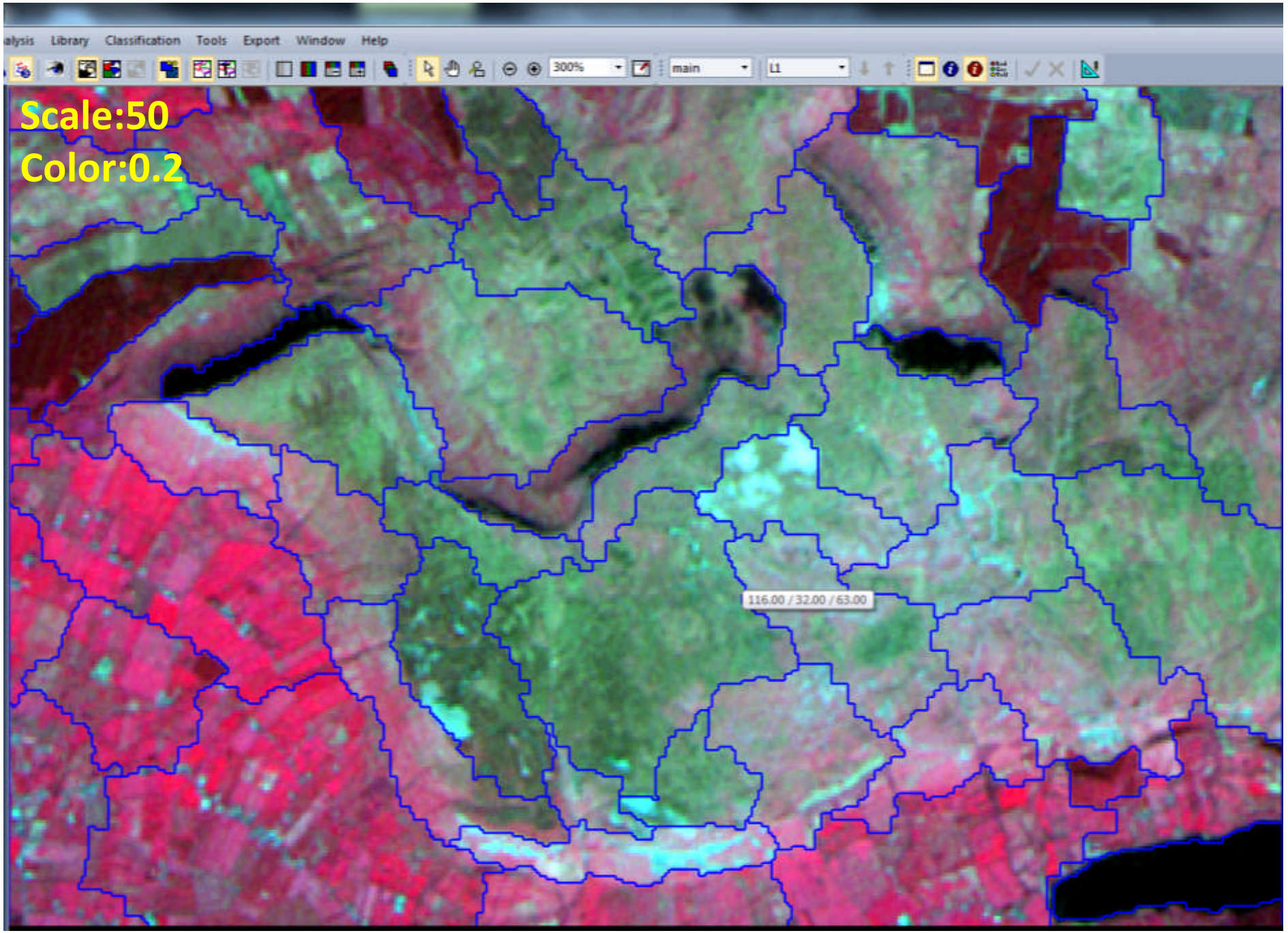
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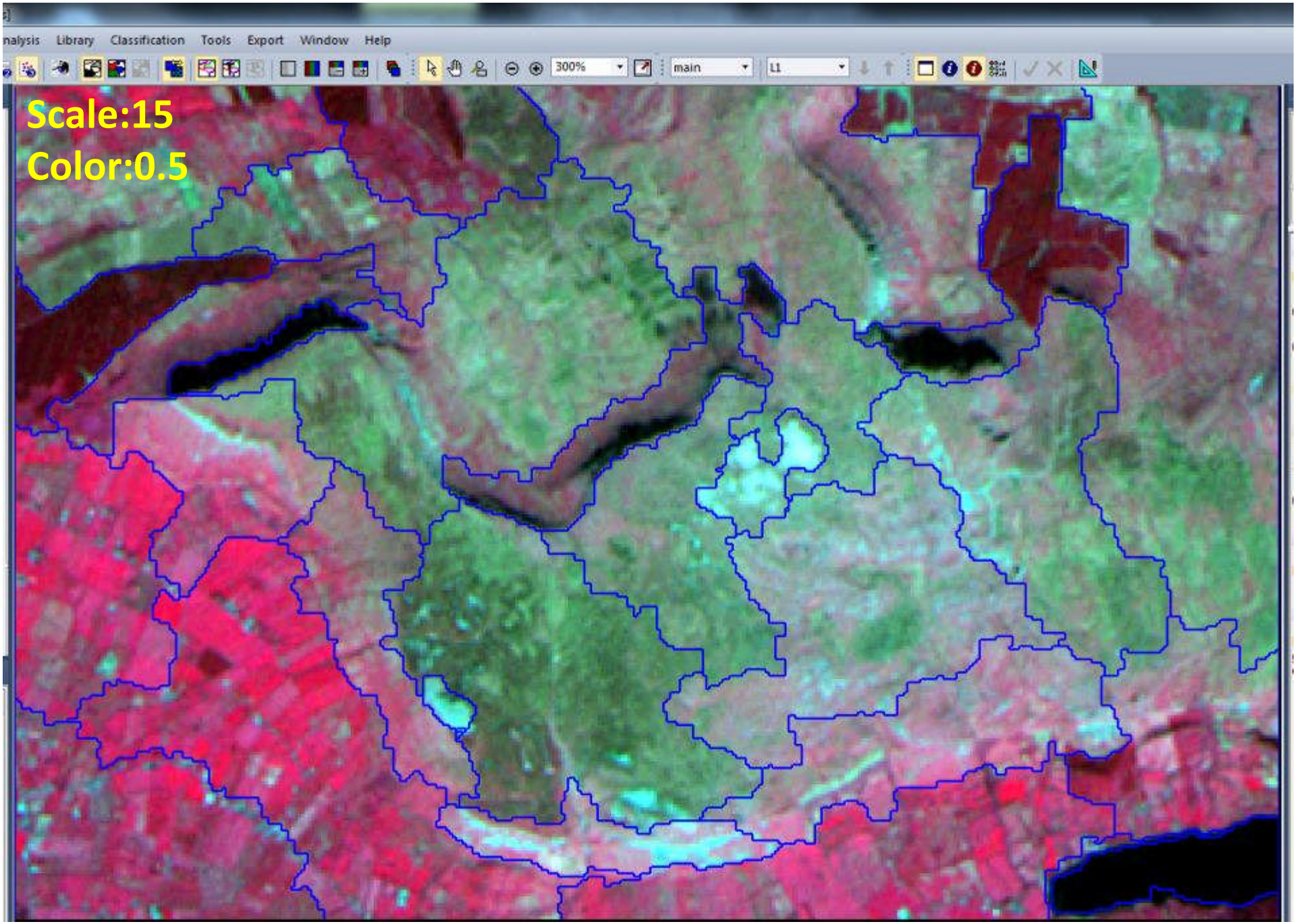
116.00 / 32.00 / 63.00


nalysis Library Classification Tools Export Window Help
300%
main
L1
Scale:15
Color:0.5

- **2.2 OBIA Strengths**
- Partitioning an image into objects is akin to the way
- humans conceptually organize the landscape to
- comprehend it.
- Using image-objects as basic units reduces computational
- classifier and at the sametime enables the user to take advantage of more complex
- techniques (e.g. non-parametric).
- Image-objects exhibit useful features that single pixels lack.
- Image-objects can be more readily integrated in vector
- GIS .
- **2.3 OBIA Weaknesses**
- There are numerous challenges involved in processing
- very large datasets. Even if OBIA is more efficient than
- pixel-based approaches, segmenting a multispectral image
- of several tens of mega-pixels is a formidable task
- Segmentation is an *ill-posed problem*, in the sense it has
- no unique solution,
- There exists a poor understanding of scale and hierarchical
- relations among objects derived at different resolutions.
- Do segments at coarse resolutions really ‘emerge’ or
- ‘evolve’ from the ones at finer resolutions? Should
- boundaries perfectly overlap (coincide) through scale?
- Operationally it’s very appealing, but what is the
- ecological basis for this?

Segmenation in ARcMAp

- **Image segmentation**
- The image segmentation is based on the Mean Shift approach. The technique uses a moving window that calculates an average pixel value to determine which pixels should be included in each segment. As the window moves over the image, it iteratively recomputes the value to make sure that each segment is suitable. The result is a grouping of image pixels into a segment characterized by an average color

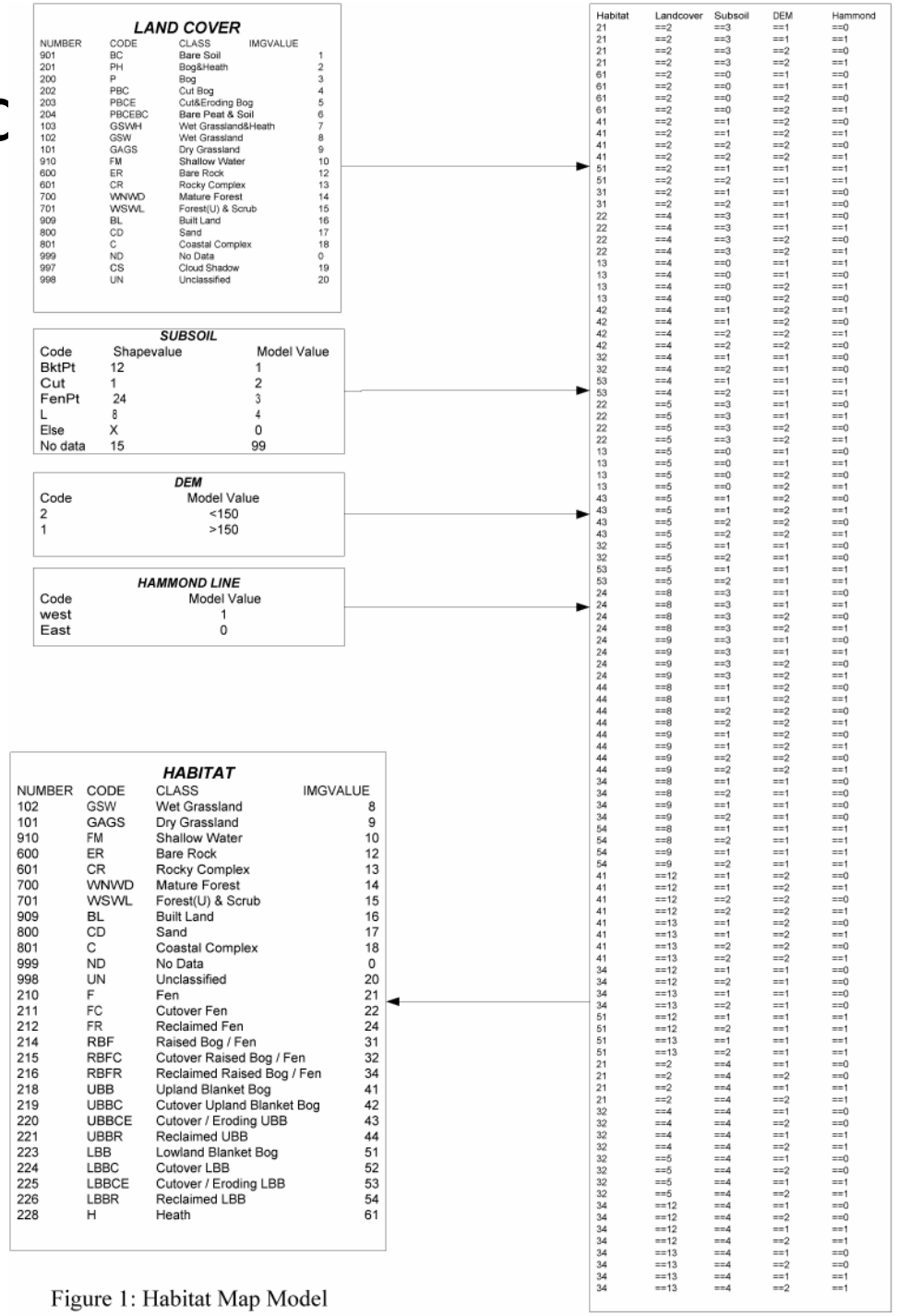
Compute Segment Attributes, supports ingest and export of segmented rasters both from and to third-party applications. This tool ingests a segmented image, a training site file, and an optional second raster to compute the attributes of each segment and output this information as an index raster file with associated attribute table.

http://desktop.arcgis.com/en/arcmap/10.3/tools/spatial-analyst-toolbox/understanding-segmentation-and-classification.htm

- The Classify Raster tool performs an image classification as specified by the Esri classifier definition file. Inputs to the tool include the image to be classified, the optional segmented raster (such as another raster dataset or a layer, such as a DEM), and a classifier definition file to generate the classified raster dataset. Note that the Classify Raster tool contains all the supported classifiers. The proper classifier is utilized depending on the properties and information contained in the classifier definition file. So the classifier definition file generated by the Train ISO Cluster Classifier, Train Maximum Likelihood Classifier, or Train Support Vector Machine Classifier will activate the corresponding classifier when you run Classify Raster

Rule or Decision basec classification

- Simplest way to bring other elements into our classification is to constrain the output based on some other dataset.



LAND COVER

NUMBER	CODE	CLASS	IMGVALUE
901	BC	Bare Soil	1
201	PH	Bog&Heath	2
200	P	Bog	3
202	PBC	Cut Bog	4
203	PBCE	Cut&Eroding Bog	5
204	PBCEBC	Bare Peat & Soil	6
103	GSWH	Wet Grassland&Heath	7
102	GSW	Wet Grassland	8
101	GAGS	Dry Grassland	9
910	FM	Shallow Water	10
600	ER	Bare Rock	12
601	CR	Rocky Complex	13
700	WNWD	Mature Forest	14
701	WSWL	Forest(U) & Scrub	15
909	BL	Built Land	16
800	CD	Sand	17
801	C	Coastal Complex	18
999	ND	No Data	0
997	CS	Cloud Shadow	19
998	UN	Unclassified	20

SUBSOIL

Code	Shapevalue	Model Value
BktPt	12	1
Cut	1	2
FenPt	24	3
L	8	4
Else	X	0
No data	15	99

DEM

Code	Model Value
2	<150
1	>150

HAMMOND LINE

Code	Model Value
west	1
East	0

HABITAT

NUMBER	CODE	CLASS	IMGVALUE
102	GSW	Wet Grassland	8
101	GAGS	Dry Grassland	9
910	FM	Shallow Water	10
600	ER	Bare Rock	12
601	CR	Rocky Complex	13
700	WNWD	Mature Forest	14
701	WSWL	Forest(U) & Scrub	15
909	BL	Built Land	16
800	CD	Sand	17
801	C	Coastal Complex	18
999	ND	No Data	0
998	UN	Unclassified	20
210	F	Fen	21
211	FC	Cutover Fen	22
212	FR	Reclaimed Fen	24
214	RBF	Raised Bog / Fen	31
215	RBFC	Cutover Raised Bog / Fen	32
216	RBFR	Reclaimed Raised Bog / Fen	34
218	UBB	Upland Blanket Bog	41
219	UBBC	Cutover Upland Blanket Bog	42
220	UBBCE	Cutover / Eroding UBB	43
221	UBBR	Reclaimed UBB	44
223	LBB	Lowland Blanket Bog	51
224	LBBC	Cutover LBB	52
225	LBBCE	Cutover / Eroding LBB	53
226	LBBR	Reclaimed LBB	54
228	H	Heath	61

Habitat	Landcover	Subsoil	DEM	Hammond
21	==2	==3	==1	==0
21	==2	==3	==1	==1
21	==2	==3	==2	==0
21	==2	==3	==2	==1
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34	==13	==4	==1	==0
34	==13	==4	==2	==0
34	==13	==4	==1	==1
34	==13	==4	==2	==1

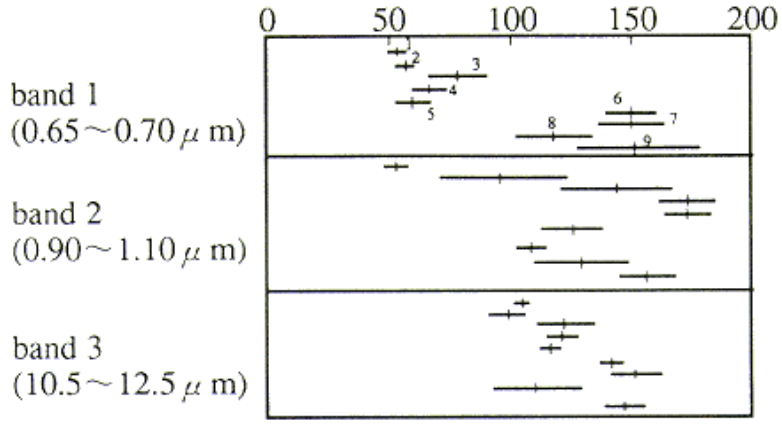
Figure 1: Habitat Map Model

Descsion tree approach

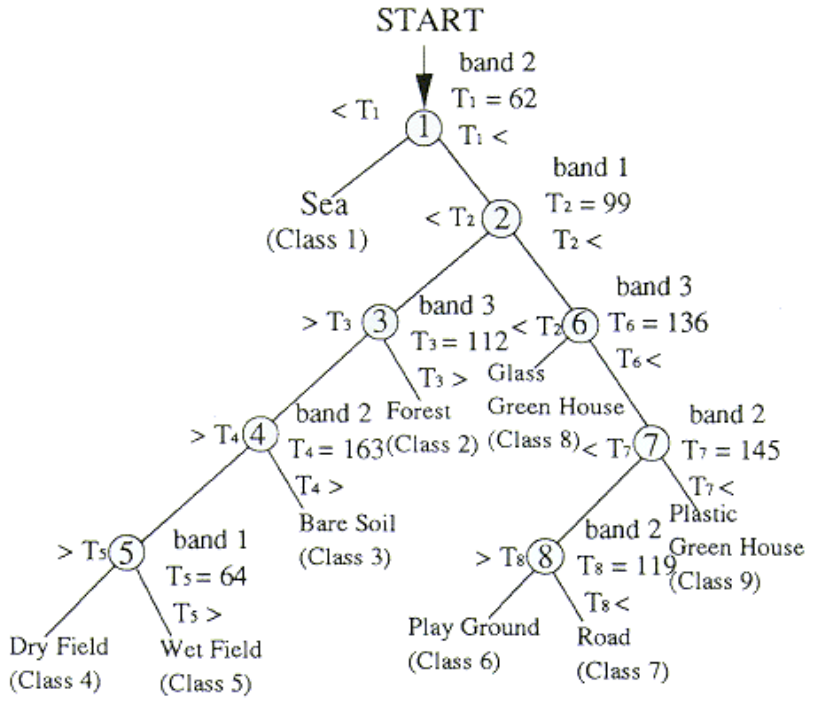
Classifies an image based on rules or thresholds of pixels values

Its akin to supervised classification but uses a non-parametric techniques to work backwards from the final classes to the orginal image based on brnahed yesy/no descesions

Simplest form of decision tree is a series of threholds



a) Spectral characteristics of nine classes



b) Decision Trees

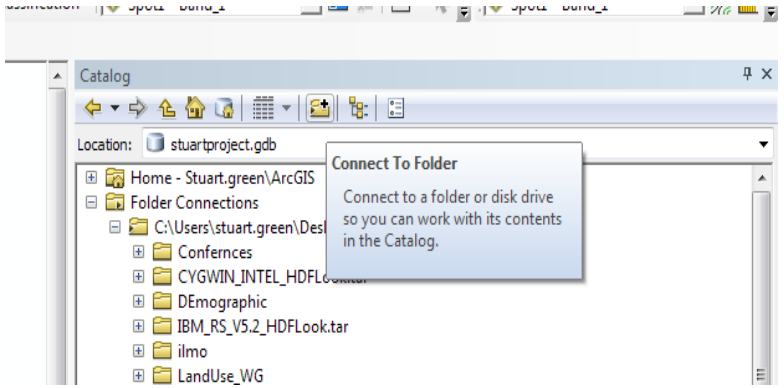
Figure 11.5.1 Hierarchical Classification by Decision Tree Classifier

In a bottom-up approach a binary tree is constructed using the training set.
Using some distance measure, such as Mahalanobis-distance, pair-wise distances between a priori
defined classes are computed and in each step the two classes with the smaller distance are merged
to form a new group.
The mean vector and the covariance matrix for each group are computed
from the training samples of classes in that group, and the process is repeated until one is left with
one group at the root.
In a tree constructed this way, the more obvious discriminations are done
first, near the root, and more subtle ones at later stages of the tree.

In top-down approaches, the design of a DTC reduces to the following three tasks:
1) The selection of a node splitting rule.
2) The decision as to which nodes are terminal.
3) The assignment of each terminal node to a class label.
Of the above three tasks, the class assignment problem is by far the easiest. Basically, to minimize
the misclassification rate, terminal nodes are assigned to the classes which have the highest probabilities. These probabilities are usually estimated by the ratio of samples from each class at that specific terminal node to the total number of samples at that specific terminal node.

ftp://piekraste.daba.lv/pub/Grafika/atteelu_analiize/MultiSpec/publications/SMC91.pdf

Setting up project inArcMap



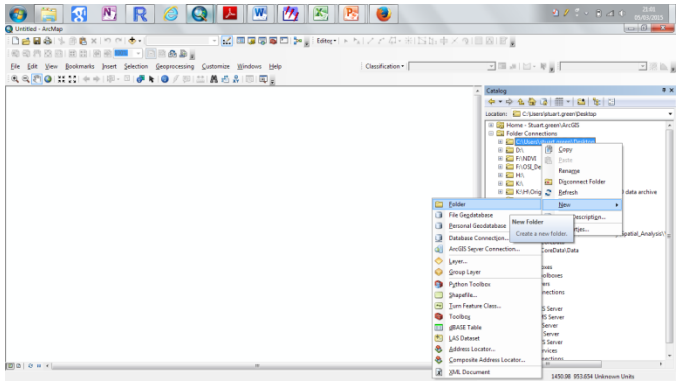
- Open blank map
- Click WINDOWS
- Click Catalogue
- Click on the Connect to Folder Button
- Add your Thumb Drive for the list of drives

Right Click on the file tree on the Thumb Drive folder-

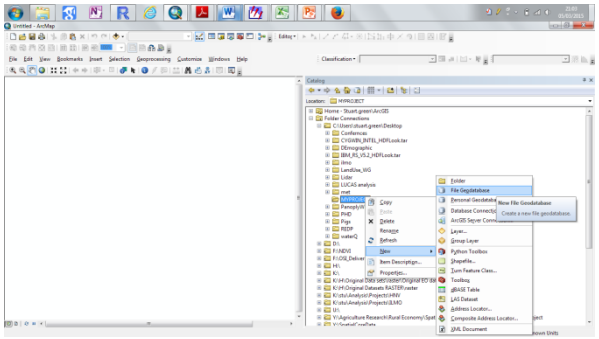
Click New

Click Folder

Create *newfolder*

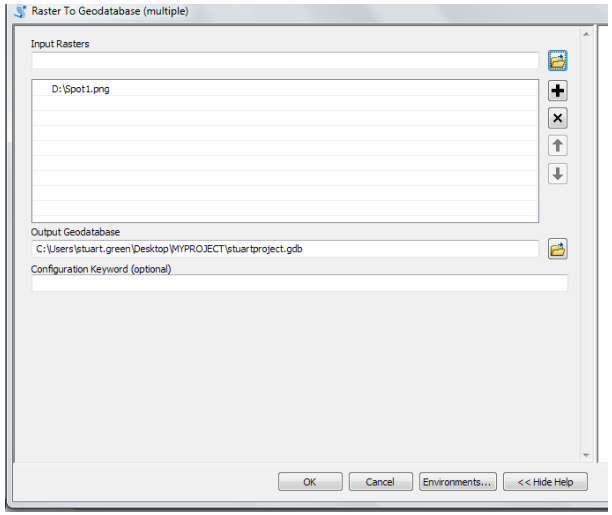


Right click on *newfolder* and create new file geodatabase- call it *mynameproject.gdb*

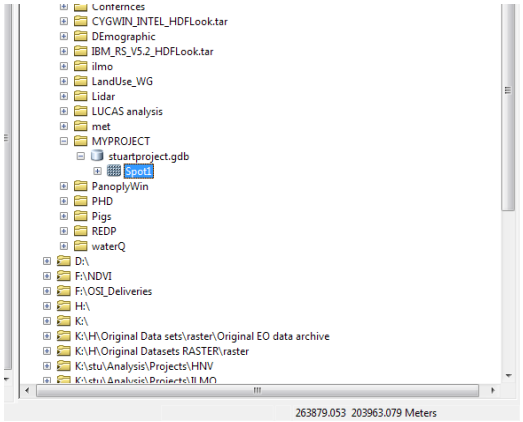


So now save all your work into this and you wont lose anything

Start by adding your Image to the Geodirectory
Ricght Click on *mynameproject.gdb* then select Import – Raster Datasets..
Make your image the Input raster and click OK

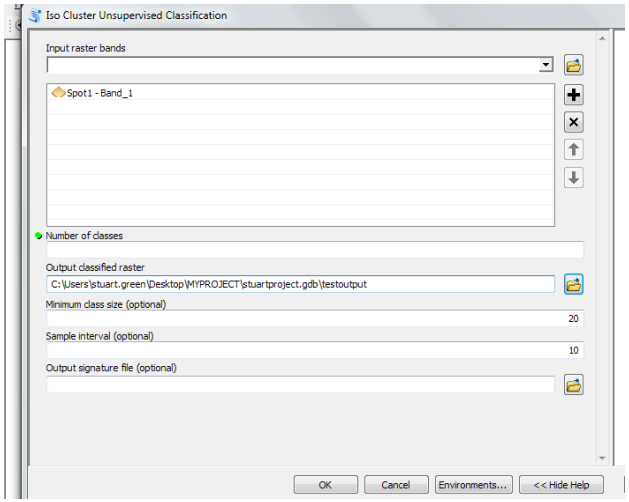


Your Image is now in your geodatabase



Lastly Save (File->Save as..) the Map document to the folder on your Thumb Drive as myproject.mxd

SAVE all you outputs and classification into mynameproject.gdb



http://verticalgeo.com/mapping/creating-a-file-geodatabase-in-arcgis-10-1/

A Simple Users Guide to selecting the right data

	Good for Continental Scale analysis	Good for National Scale	Good for county area coverage	Good for seeing farm scale detail	Good for seeing Sub-field scale detail	Good for Historical Change analysis	Good for real time change detection	Good for Broad vegetation classes	Good for distinguishing habitats	Good for species/genus level distinction	Ready to Use	Free	Needs atmospheric Correction
Landsat 8 Level 2a		Y	Y	Y		Y		Y	Y		Y	Y	
MODIS	Y	Y	Y			Y	Y	Y			Y	Y	
Spot 4/5		Y	y	y		y		y			y		y
Spot 6/7 PS		y	y	y	y			y			y		y
Sentinel 2		y	y	y			y	y	y		y	y	y
LISS		y	y					y			y		y
Eo-1				y				y	y	y		y	y
WorldView 2/ GeoEye				y	y			y			y		
IKONOS				Y	Y			Y			Y		
Rapid Eye			Y	Y				Y			Y		Y