URBAN LAND-USE MULTI-SCALE TEXTURAL ANALYSIS

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Urban areas currently cover only 2% of the land surface, but they have a **global impact** due to the size of the demand associated to:

- energy
- food
- water
- raw material

The analysis of the urban environment represents one of the most important areas for the remote sensing community.

Urban areas are composed of numerous materials:

concrete, asphalt, metal, plastic, glass, water, grass, shrubs, trees and soil

arranged by humans in complex ways to build housing, transportation systems, utilities, commercial buildings and recreational areas.

Introduction (2/3)

Very high resolution panchromatic images, such those provided by **QuickBird**, **WorldView 1** and future **WorldView 2**, have the potential for an increase in accurate mapping of the urban environment with a **sub-meter** ground resolution.

It is necessary to extract additional information from panchromatic data to recognize objects within the scene, such as morphological or textural features.

Although more information may be helpful for the classification process, it could introduce other problems:

- "curse" of dimensionality
- increase of computation time

This results in a necessity to estimate the contribution of each parameter in order to reduce and optimize the input space.

A multi-scale textural analysis is presented to optimize the classification process of urban land-use in very high spatial resolution panchromatic imagery.

Location	Acquisition Date	Satellite	Spat. Res. (m)	Dim. (pixels)
Las Vegas, U.S.A.	May 10, 2002	QuickBird	0.6	755x722
Rome, Italy	July 19, 2004			1188x973
Washington, U.S.A.	December 18, 2007	WorldView 1	0.5	2173x2103
San Francisco, U.S.A.	November 26, 2007			917x889

Outline

1. Classification performance for Las Vegas, Rome and Washington:
   - panchromatic data
   - multi-scale textural features + NN topology optimization
   - multi-scale textural features + NN extended pruning

   → to give evidence of the most relevant input features

2. Analysis of the input feature contributions for the 3 data sets:
   - extraction of the most significant features
   - application of the resulting parameters to an independent data set (San Francisco)

3. Analysis of texture properties of shadowed areas

4. Conclusions

Las Vegas – Data Set and Regions Of Interest

Urban environment with regular structures

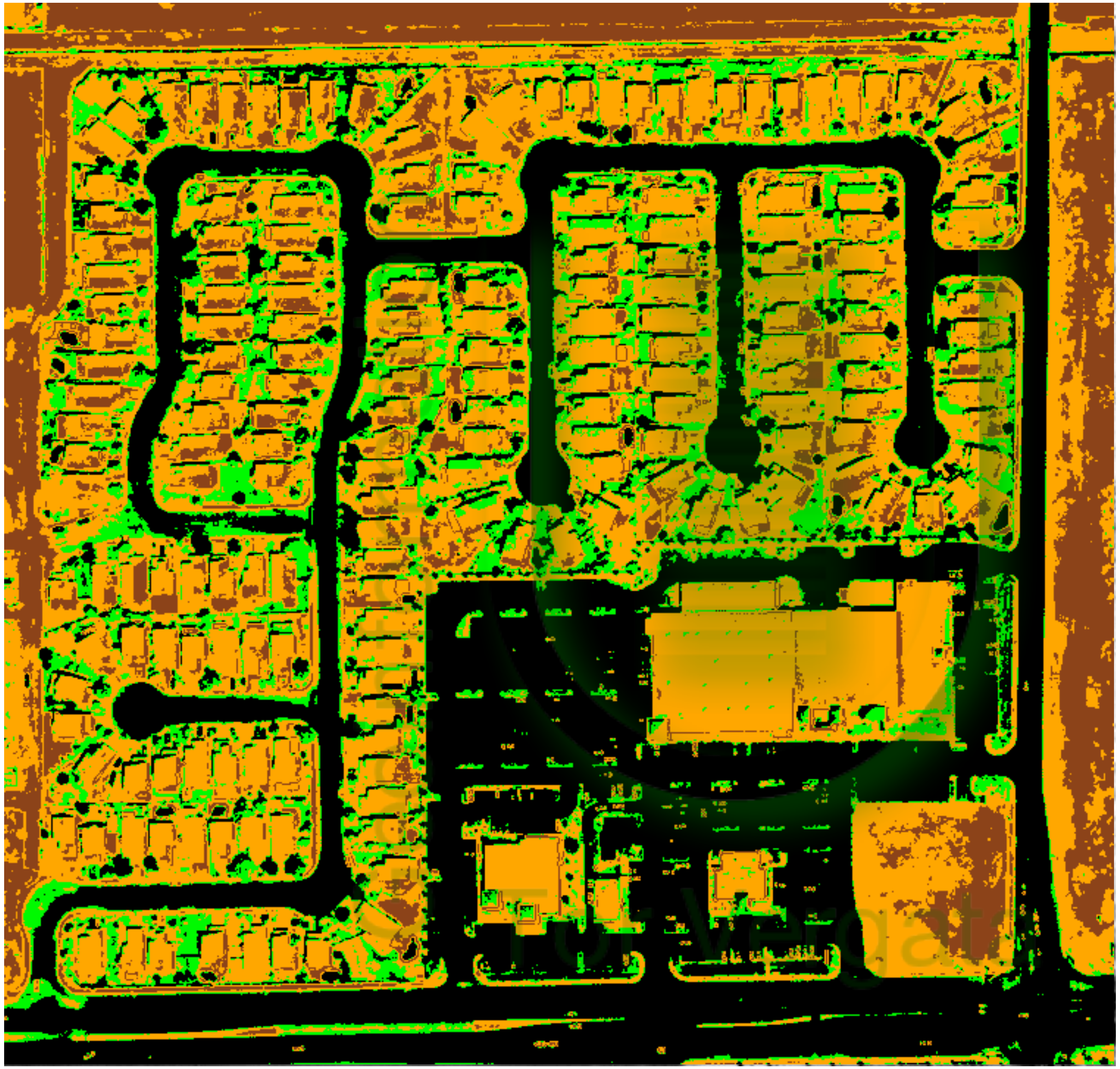
Presence of cars in the parking lots

Small shadows

Medium off-nadir angle (12.8°)

Land-Use Classes	TR	VS
Bare Soil	4255	44675
Commercial Buildings	1822	19126
Drainage Channel	1143	12001
Highway	2836	29774
Parking Lots	2257	23695
Residential Houses	7007	73563
Roads	6098	64023
Short Vegetation	1793	18823
Soil	1472	15437
Trees	1043	10945
Water	118	1236
TOTAL ROIs	29844	313298

Las Vegas – Classification Map (Panchromatic ONLY)

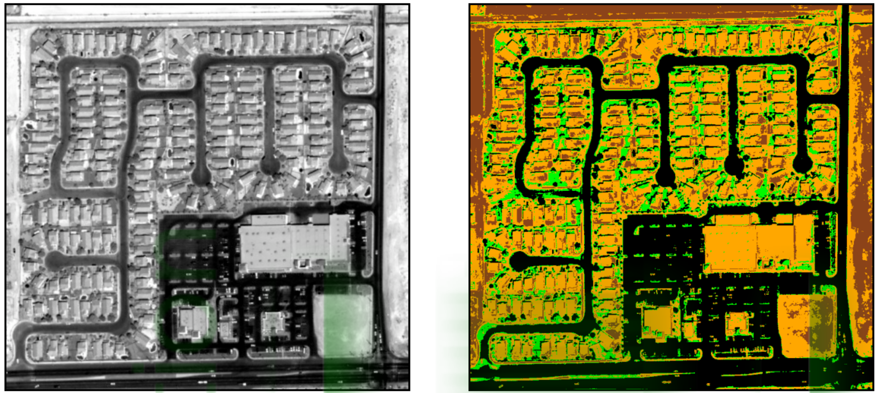


Land-Use Classes	
	Bare Soil
	Commercial Buildings
	Drainage Channel
	Highway
	Parking Lots
	Residential Houses
	Roads
	Short Vegetation
	Soil
	Trees
	Water

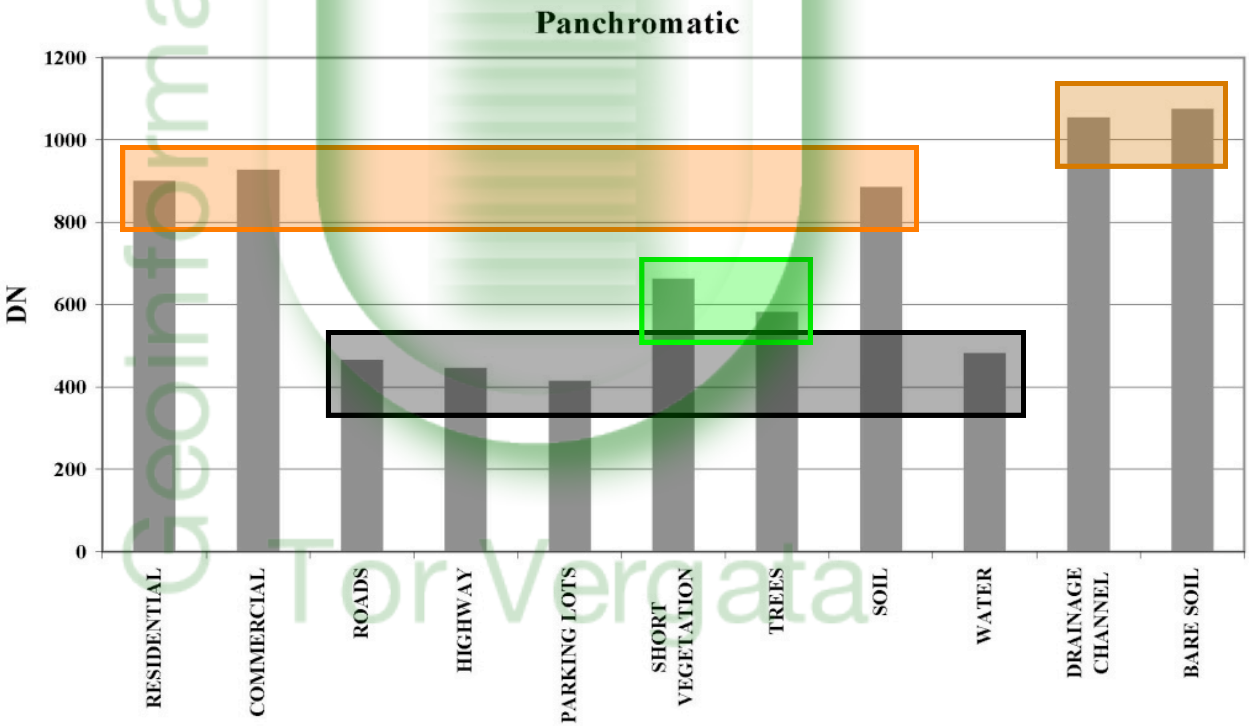
Overall Error = 50.2%

k-Coeff. = 0.378

Las Vegas – Analysis of DG



Land-Use Classes	
	Bare Soil
	Residential Houses
	Roads
	Short Vegetation



Texture Features Definition

We analyze the contextual information of each pixel by mean textural features.

	Input Features	Cell Size (pixel)	Step (pixel)	Direction (°)	# Inputs
	Panchromatic				1
First-order	Mean Variance	3x3 7x7 15x15 31x31 51x51			10
Second-order	Homogeneity Contrast Dissimilarity Entropy Second Moment Correlation	3x3 7x7 15x15 31x31 51x51	15 30	0 45 90	180
				Total Input Features	191

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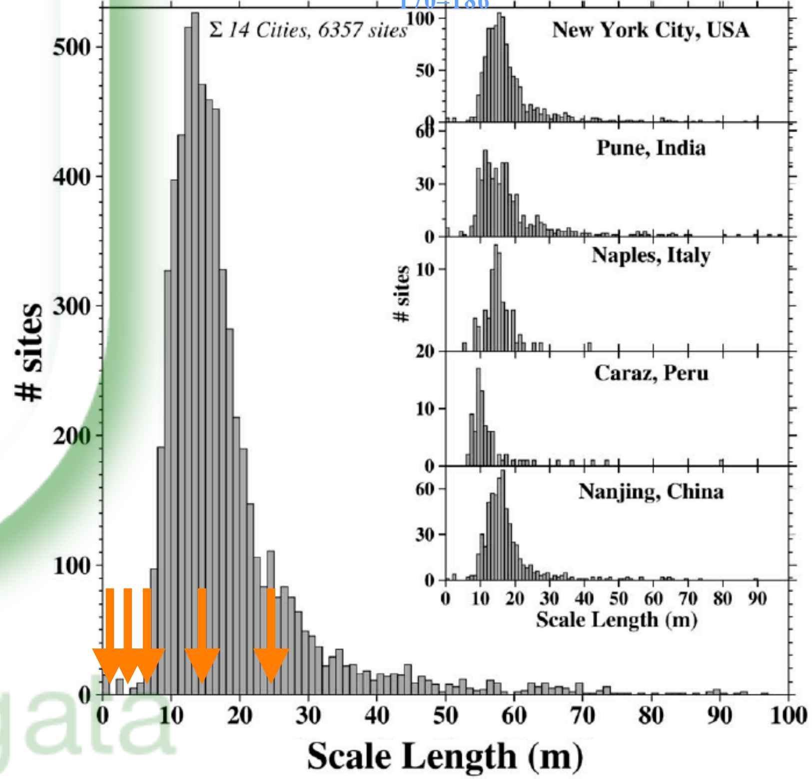
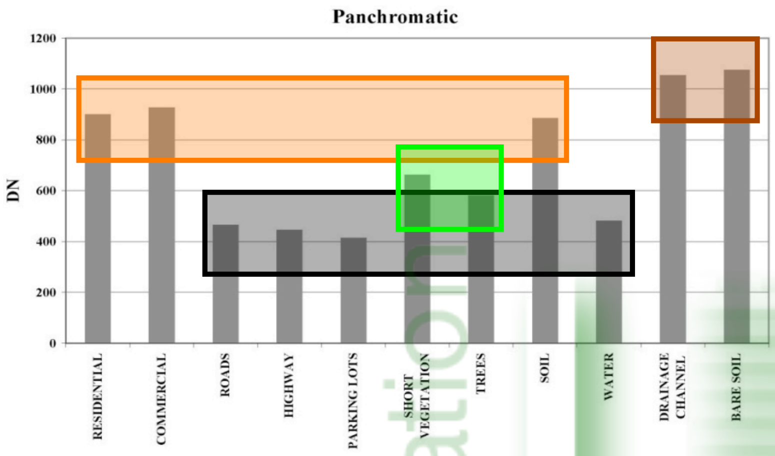
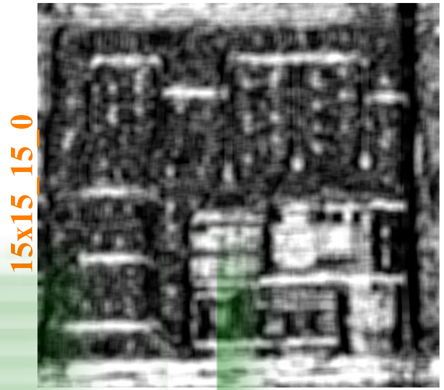


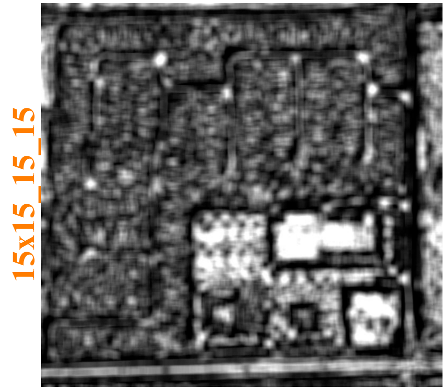
Las Vegas – Homogeneity

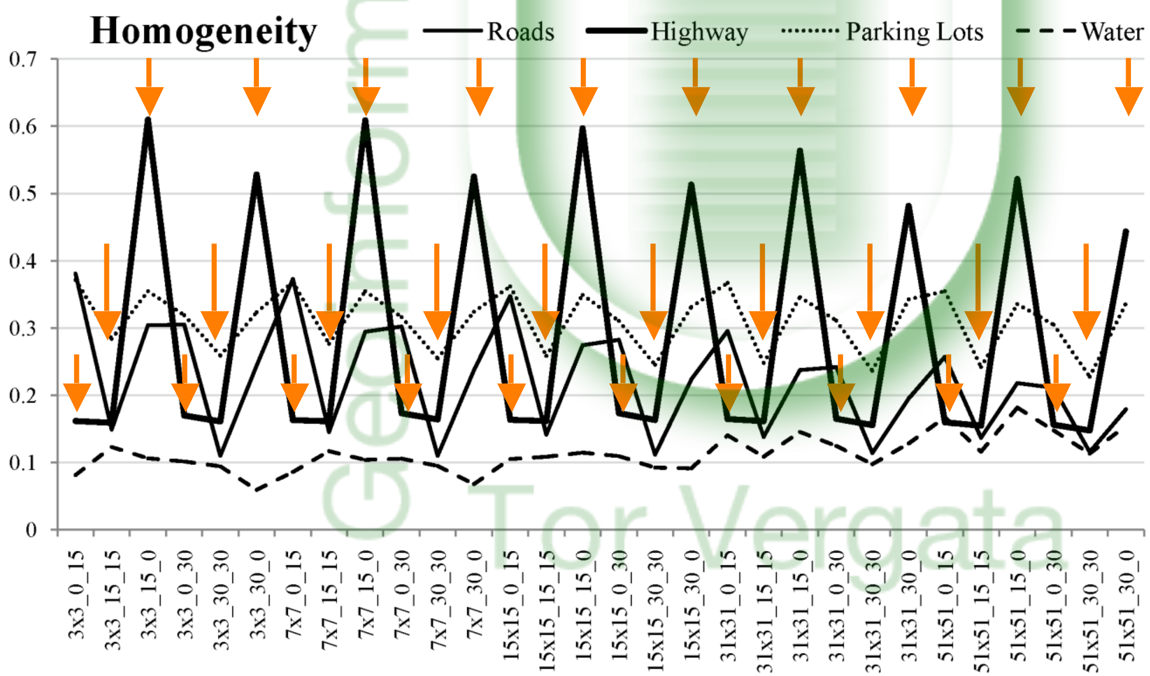


Horizontal structures

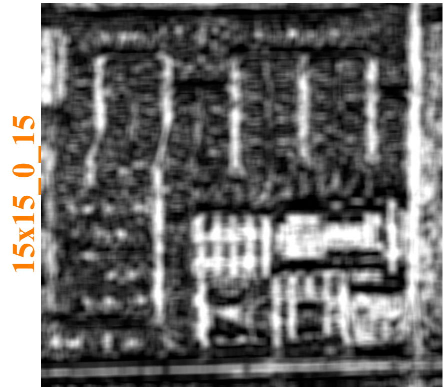


Wide structures





Vertical structures



Homogeneity assumes larger values for smaller gray tone differences in pair elements.

Las Vegas – Optimum Classification Map (1/2)

The classification process with a large input space **rarely** yields high classification accuracies due to **information redundancy** of certain inputs.

Neural network pruning eliminates the weakest connections and at the same time optimizes the network topology:

→ generally, this increases the classification accuracy.

Neural network pruning was used to eliminate the textural features that **did not** contribute to the classification process

→ i.e. textural features that introduce ONLY redundancy.

The remaining input features totaled 169.

Las Vegas – Optimum Classification Map (2/2)

Land-Use Classes
Bare Soil
Commercial Buildings
Drainage Channel
Highway
Parking Lots
Residential Houses
Roads
Short Vegetation
Soil
Trees
Water

Overall Error = 6.8%

***k*-Coeff. = 0.920**

Rome – Data Set and Regions Of Interest

2 Different urban environments:
- old style architecture
- new style architecture

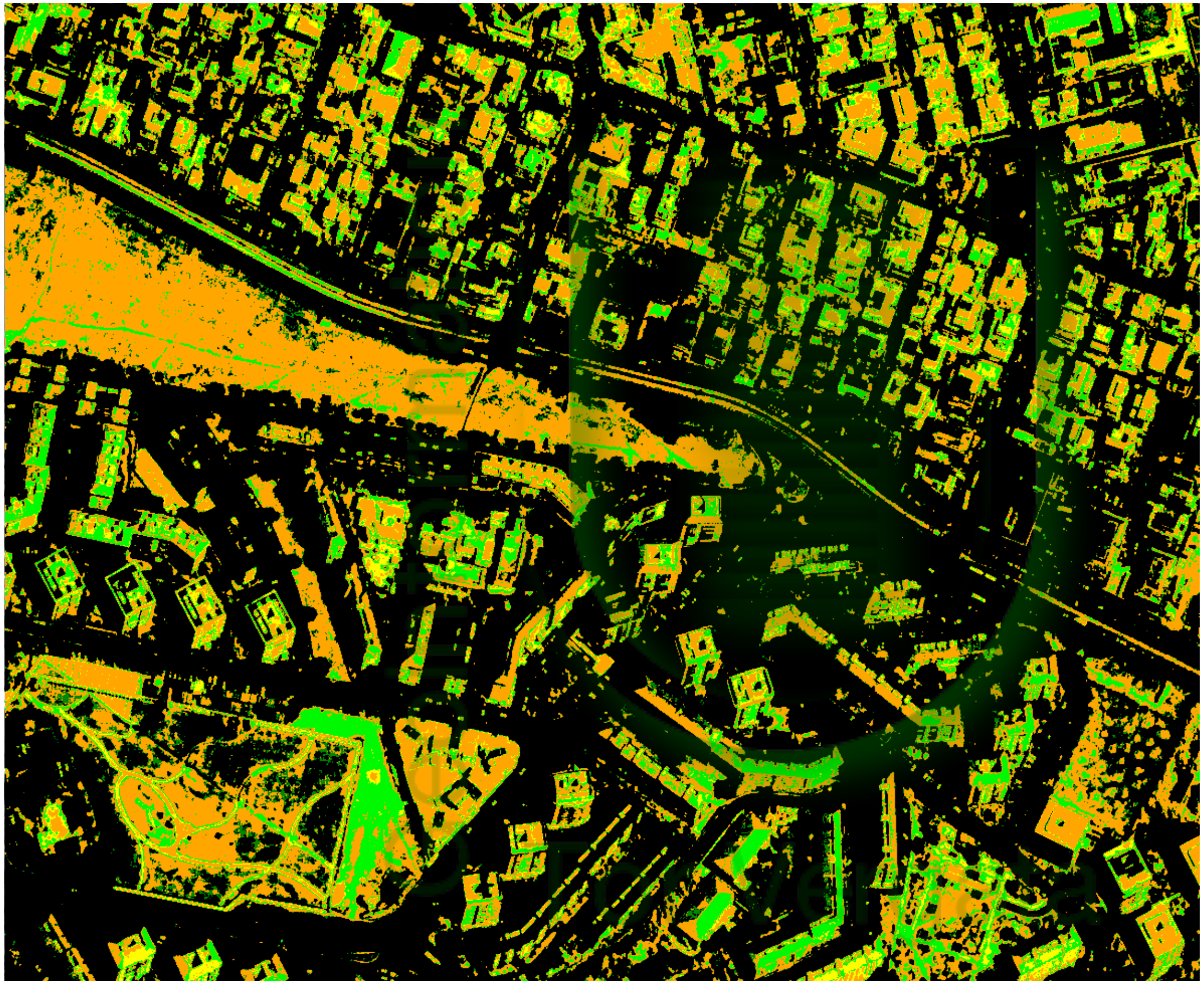
Many temporary objects:
- cars
- buses

Long shadows

High off-nadir angle (23°)

Land-Use Classes	TR	VS
Bare Soil	4127	38572
Apartment Blocks	20472	44672
Buildings	27188	77034
Railway	2606	6727
Roads	35531	69002
Soil	3506	5776
Tower	9187	19365
Trees	13632	38624
Short Vegetation	10443	29587
TOTAL ROIs	126692	329359

Rome – Classification Map (Panchromatic ONLY)



Land-Use Classes
Bare Soil
Apartment Blocks
Buildings
Railway
Roads
Soil
Tower
Trees
Short Vegetation

Overall Error = 66.0%

***k*-Coeff. = 0.184**

Rome – Optimum Classification Map

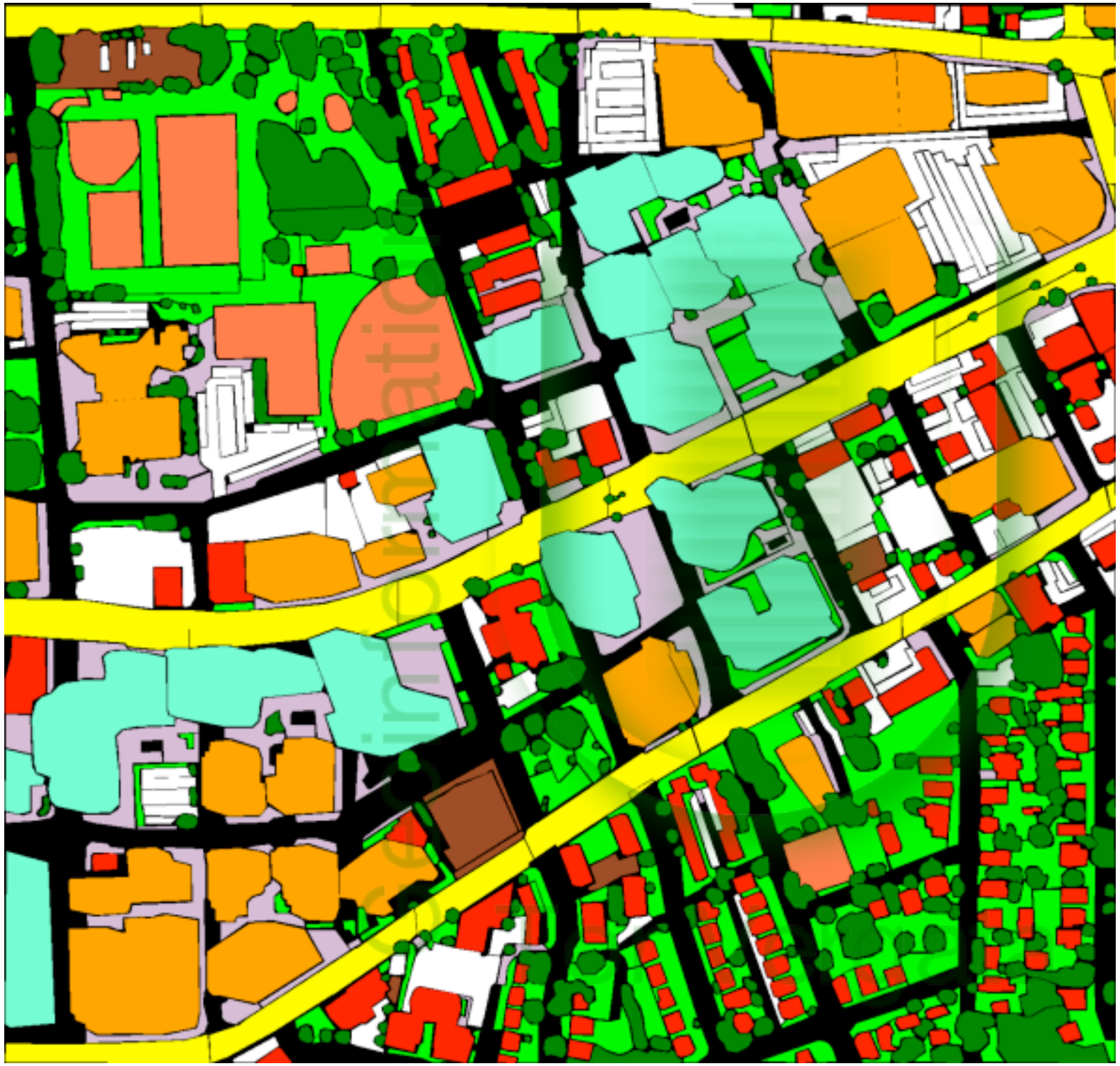
Again, pruning was applied to reduce the number of textural features eliminating the redundant inputs. The selected input features were 140.

Land-Use Classes
Bare Soil
Apartment Blocks
Buildings
Railway
Roads
Soil
Tower
Trees
Short Vegetation

Overall Error = 5.0%

***k*-Coeff. = 0.941**

Washington – Data Set and Regions Of Interest



3 Different urban environments:
- small residential houses
- large buildings
- tall large buildings

Very long shadows
(24.9° sun elevation)

Very high off-nadir angle
(27.8°)

Land-Use Classes	TR	VS
Buildings	24178	76159
Highway	17985	56653
Parking Lots	17019	53611
Residential	14195	44714
Roads	20618	64946
Soil	2553	8043
Sport Facilities	8270	26051
Tall Buildings	21047	66297
Trees	18535	58386
Short Vegetation	23403	73720
Walk side	12203	38439
TOTAL ROIs	180006	567019

Washington – Classification Map (Panchromatic ONLY)

Land-Use Classes	
	Buildings
	Highway
	Parking Lots
	Residential
	Roads
	Soil
	Sport Facilities
	Tall Buildings
	Trees
	Short Vegetation
	Walk side

Overall Error = 68.6%

***k*-Coeff. = 0.187**

Washington – Optimum Classification Map

Land-Use Classes
Buildings
Highway
Parking Lots
Residential
Roads
Soil
Sport Facilities
Tall Buildings
Trees
Short Vegetation
Walk side

Overall Error = 8.6%

***k*-Coeff. = 0.904**

Feature selection

Feature selection with neural networks can be seen as a special case of architecture pruning.

EXTENDED PRUNING is the process of eliminating the **least contributing inputs** in order to identify an optimal textural feature set:

this further input textural feature reduction results in a decrease in the classification accuracy.

	LAS VEGAS			ROME			WASHINGTON DC		
	Class. Err. (%)	*k*-Coeff.	Inputs	Class. Err. (%)	*k*-Coeff.	Inputs	Class. Err. (%)	*k*-Coeff.	Inputs
Panchromatic	50.2	0.378	1	66.0	0.184	1	68.6	0.187	1
Full NN	7.1	0.916	191	16.9	0.798	191	14.5	0.838	191
Pruned NN	6.8	0.920	169	5.0	0.941	140	8.6	0.904	152
Ext. Pruning	12.0	0.859	59	15.1	0.820	61	18.31	0.796	59

Feature Contribution

A simple method of determining the relative significance of the input features once the network has been trained considers the most important input units those that have the largest absolute values of weighted connections.

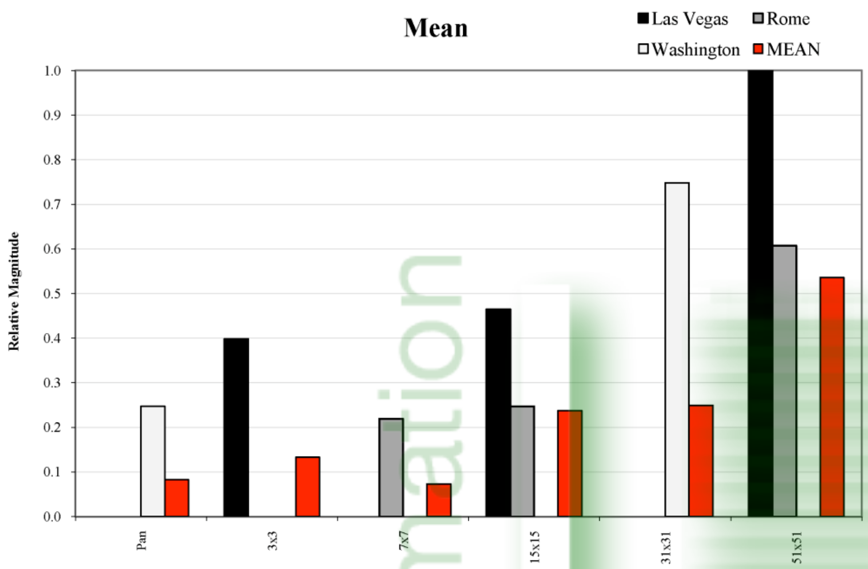
In the case of two hidden layers, a saliency metric for the single feature input *i* with respect to the class *j* is given by:

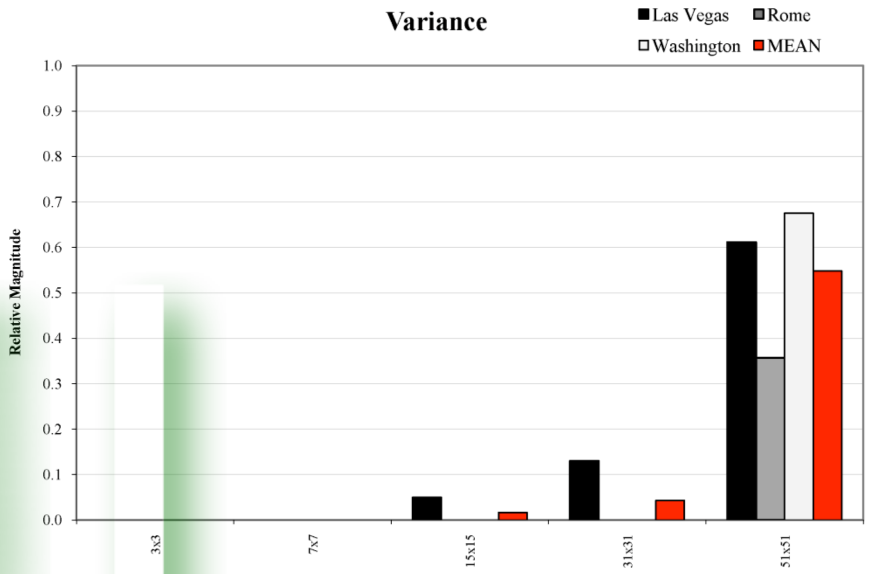
$$S_{ij} = \sum_{k \in H1} \left[\frac{|w_{ik}|}{\sum_{k' \in H1} |w_{ik'}|} \cdot \sum_{x \in H2} \left(\frac{|w_{kx}||w_{xj}|}{\sum_{x' \in H2} |w_{kx'}| \cdot \sum_{x' \in H2} |w_{x'j}|} \right) \right]$$

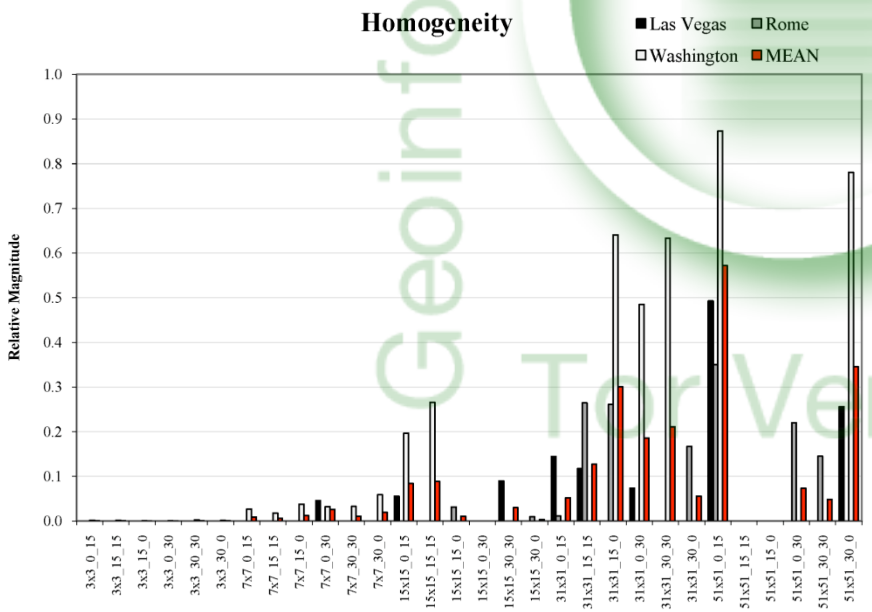
The relevance (*contribution*) of the input feature *i* with respect to all output classes is given by:

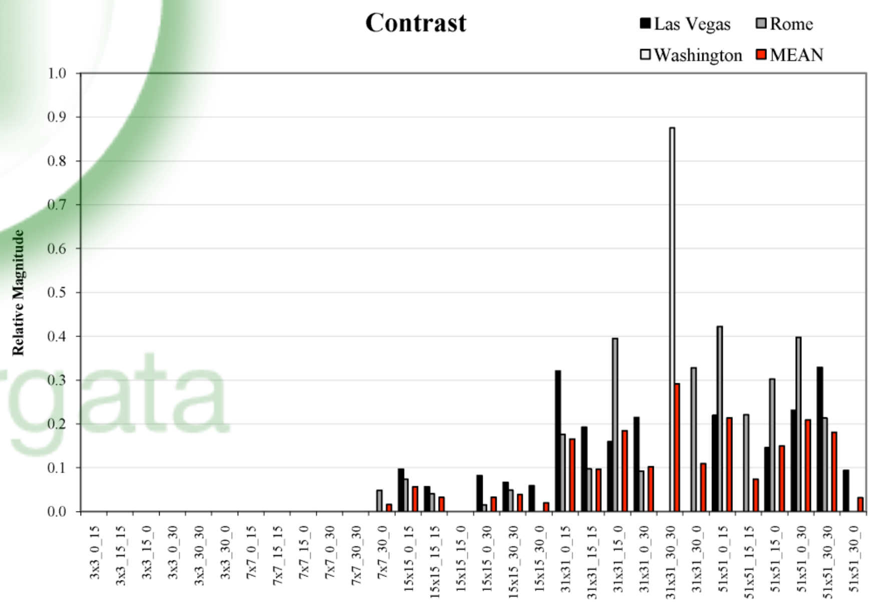
$$S_i = \sum_{j=1}^{N_{cl}} S_{ij}$$

Extended Pruning (1/2)

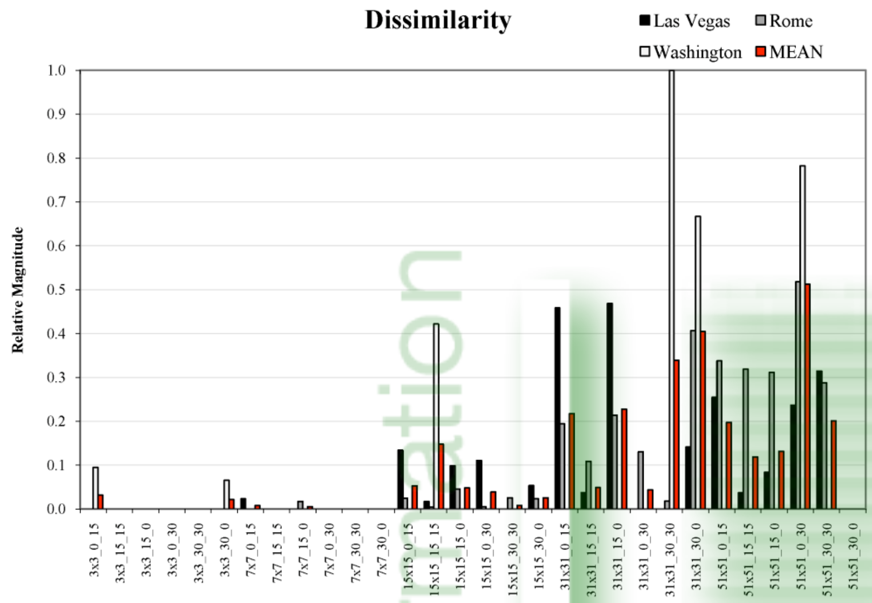


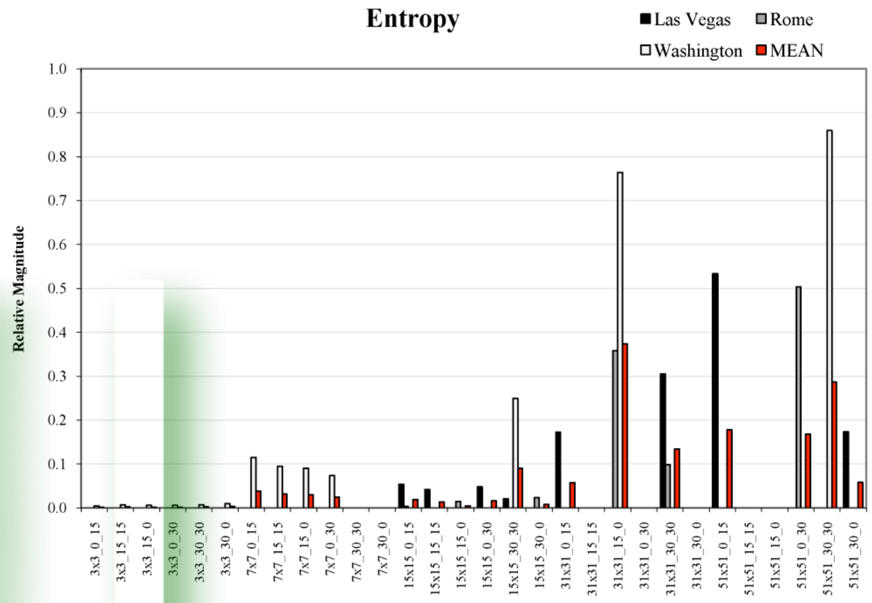


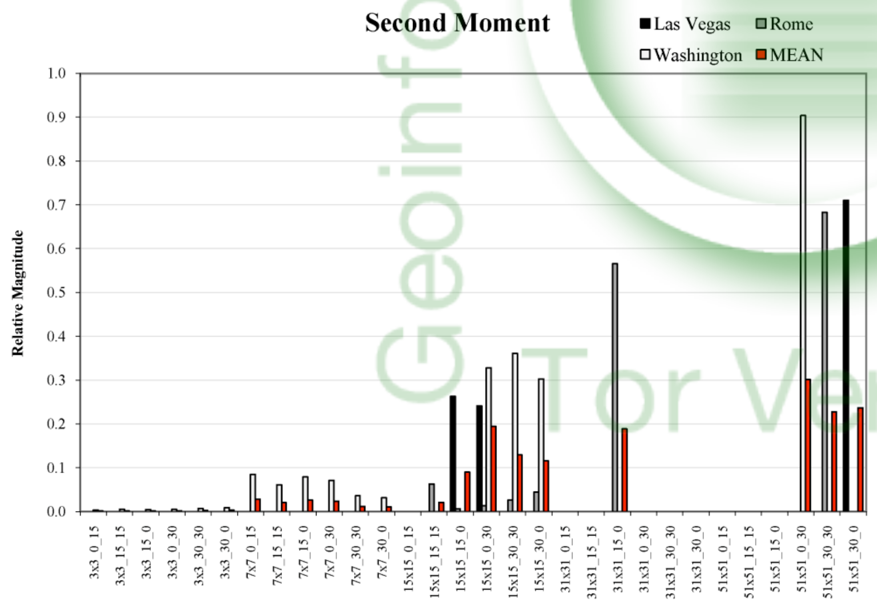


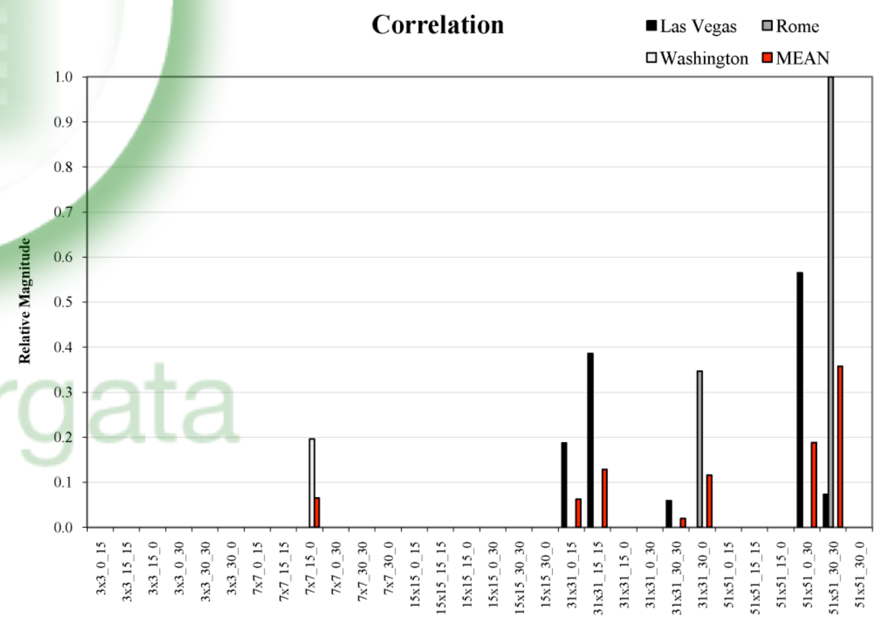


Extended Pruning (2/2)



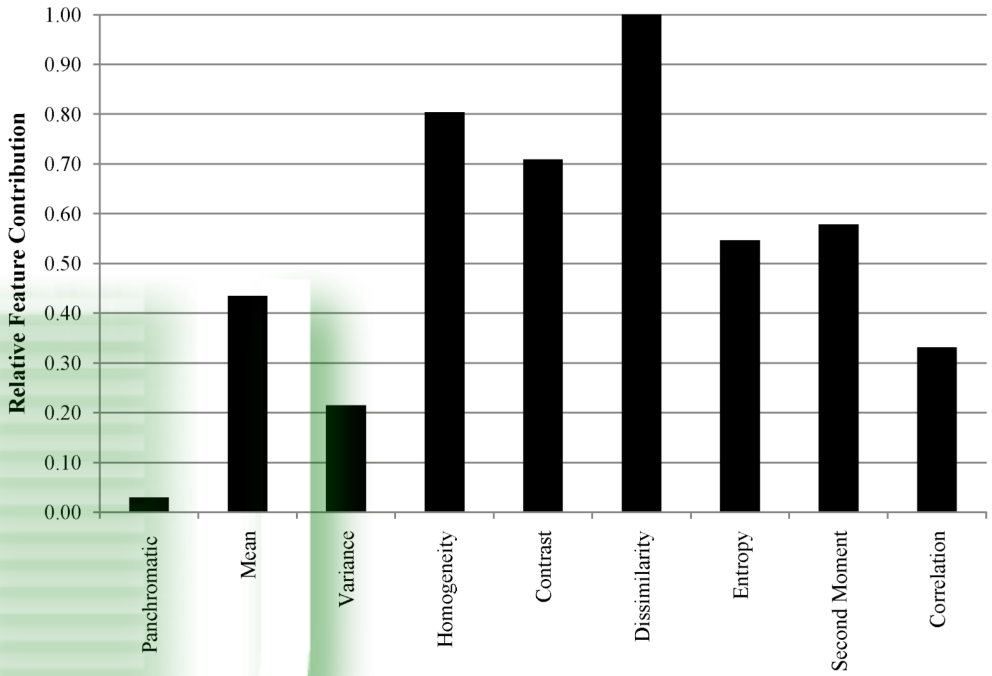




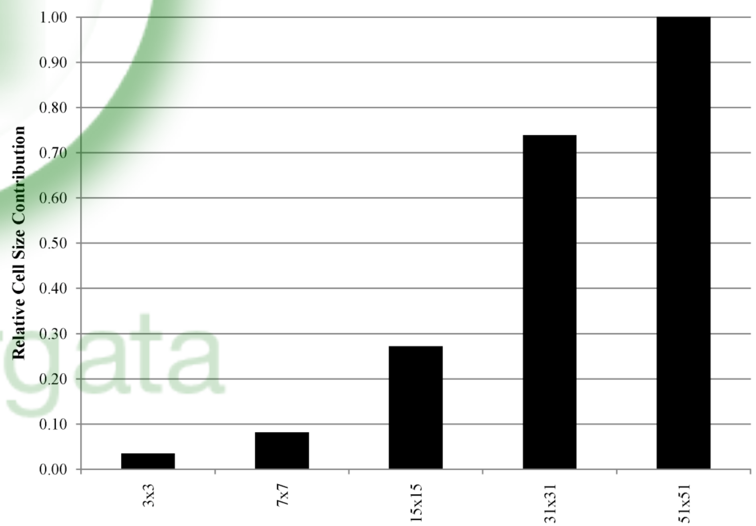


Textural Analysis – features-cell sizes-directions

Input Features	Relative Feature Contribution
Panchromatic	0.029
Mean	0.434
Variance	0.214
Homogeneity	0.803
Contrast	0.708
Dissimilarity	1.000
Entropy	0.546
Second Moment	0.577
Correlation	0.331

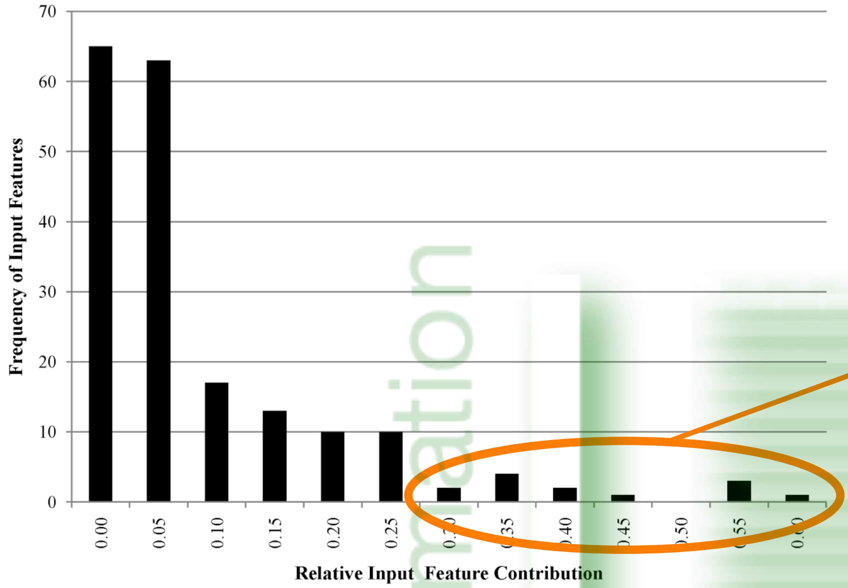


Cell size	Relative Contribution
3x3	0.034
7x7	0.081
15x15	0.272
31x31	0.738
51x51	1.000



Direction	Relative Contribution
90	1.000
45	0.923
0	0.821

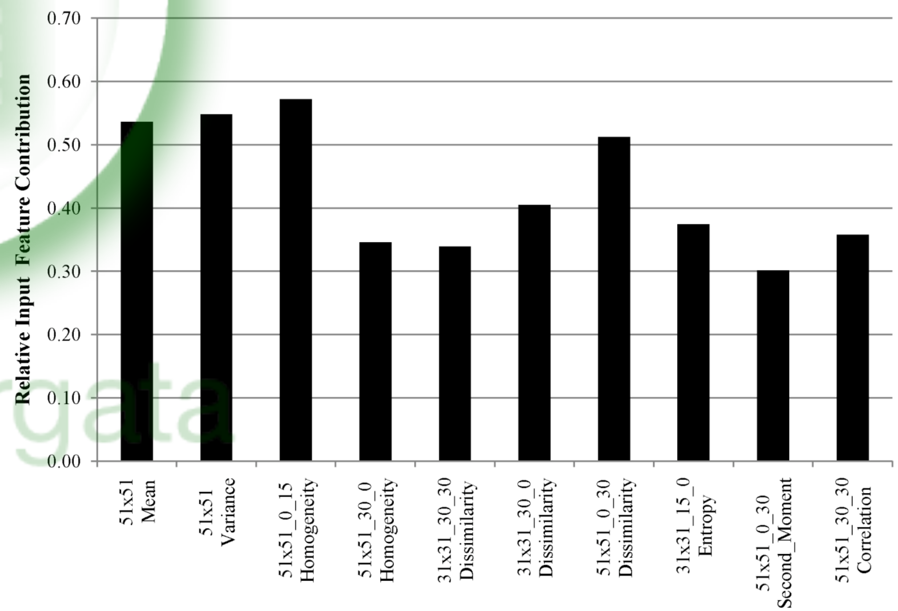
Textural Analysis – most significant features



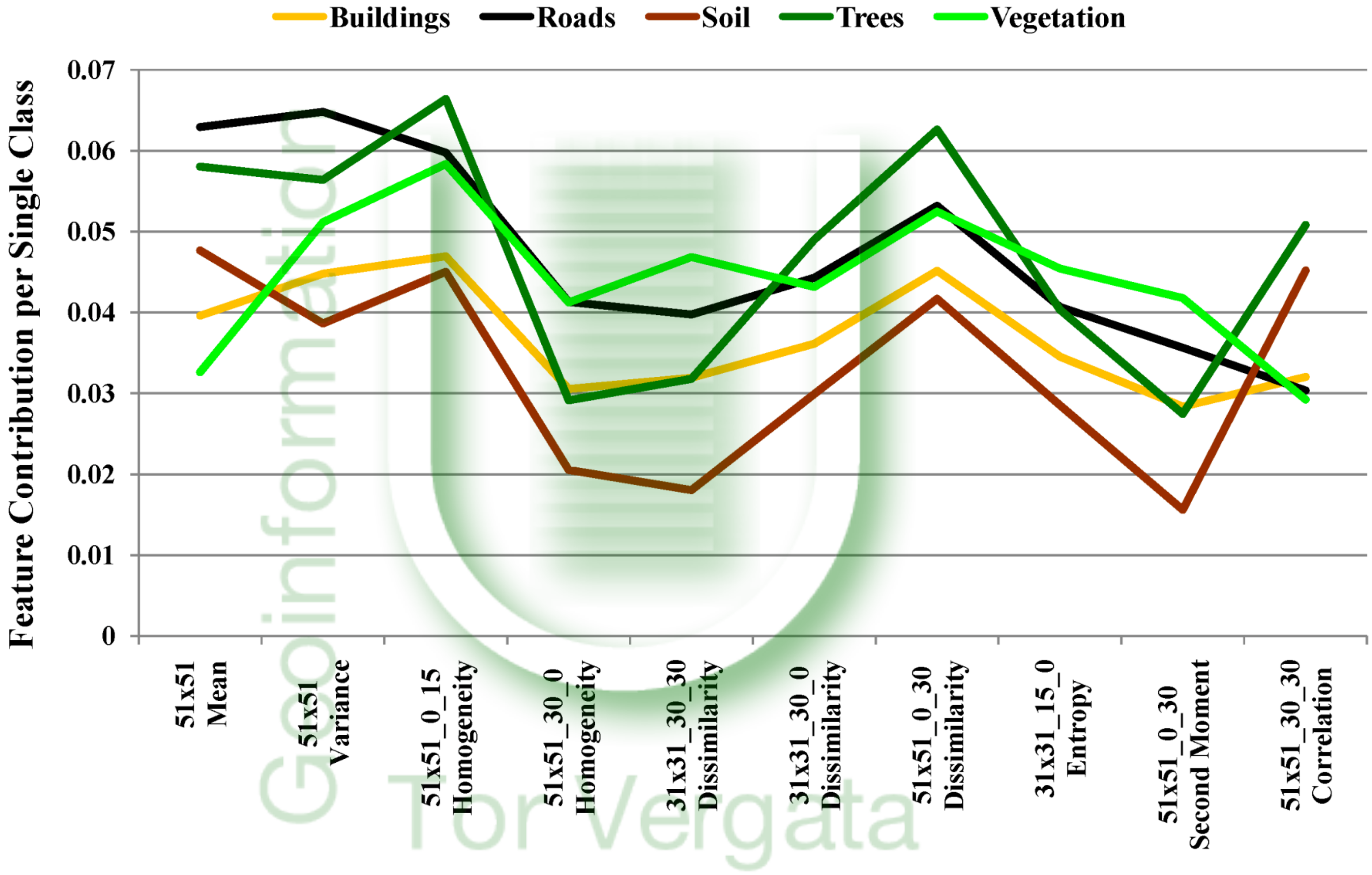
Best 10 features	Relative Input Feature Contribution
Mean 51x51	0.535
Variance 51x51	0.547
Homogeneity 51x51_0_15	0.572
Homogeneity 51x51_30_0	0.345
Dissimilarity 31x31_30_30	0.339
Dissimilarity 31x31_30_0	0.404
Dissimilarity 51x51_0_30	0.512
Entropy 31x31_15_0	0.374
Second Moment 51x51_0_30	0.301
Correlation 51x51_30_30	0.357

Which is the contribution per single class of these 10 features?

i.e. which feature should one use for a particular class?



Textural Analysis – common classes



Washington image: **Overall Error = 9.7%** ***k*-Coeff. = 0.861**

San Francisco – Data Set and Regions Of Interest

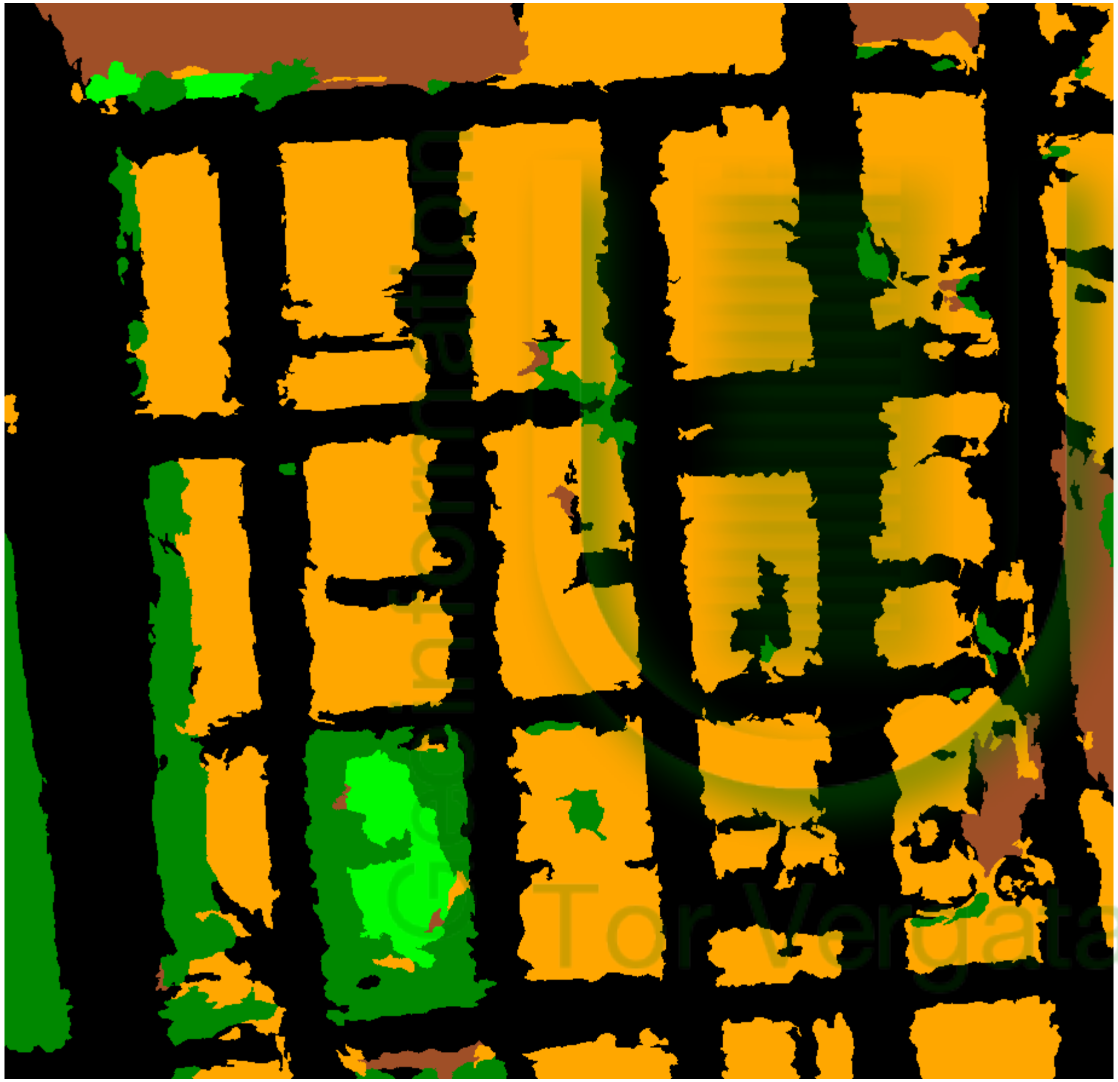
How well do these 10 features classify a new urban scene?

Long shadows
(29.6° sun elevation)

High off-nadir angle
(19.6°)

Classes	TR	VS
Buildings	36,689	85,240
Roads	49,436	114,857
Soil	6,524	15,158
Trees	7,745	17,993
Vegetation	1,465	3,404
TOTAL ROIs	101,859	236,652

San Francisco – Classification Map



Land-cover Classes	
	Buildings
	Roads
	Soil
	Trees
	Vegetation

Overall Error = 5.1%

***k*-Coeff. = 0.917**

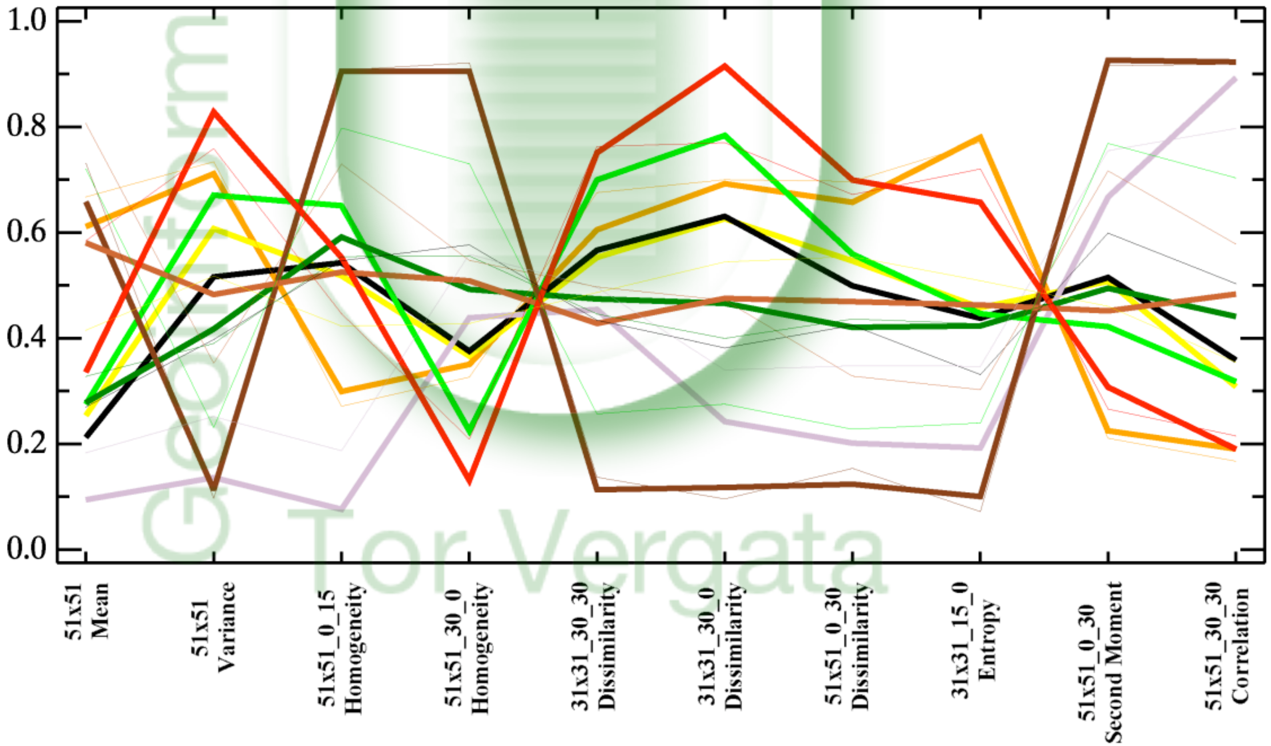
Panchromatic ONLY:

Overall Error = 42.8%

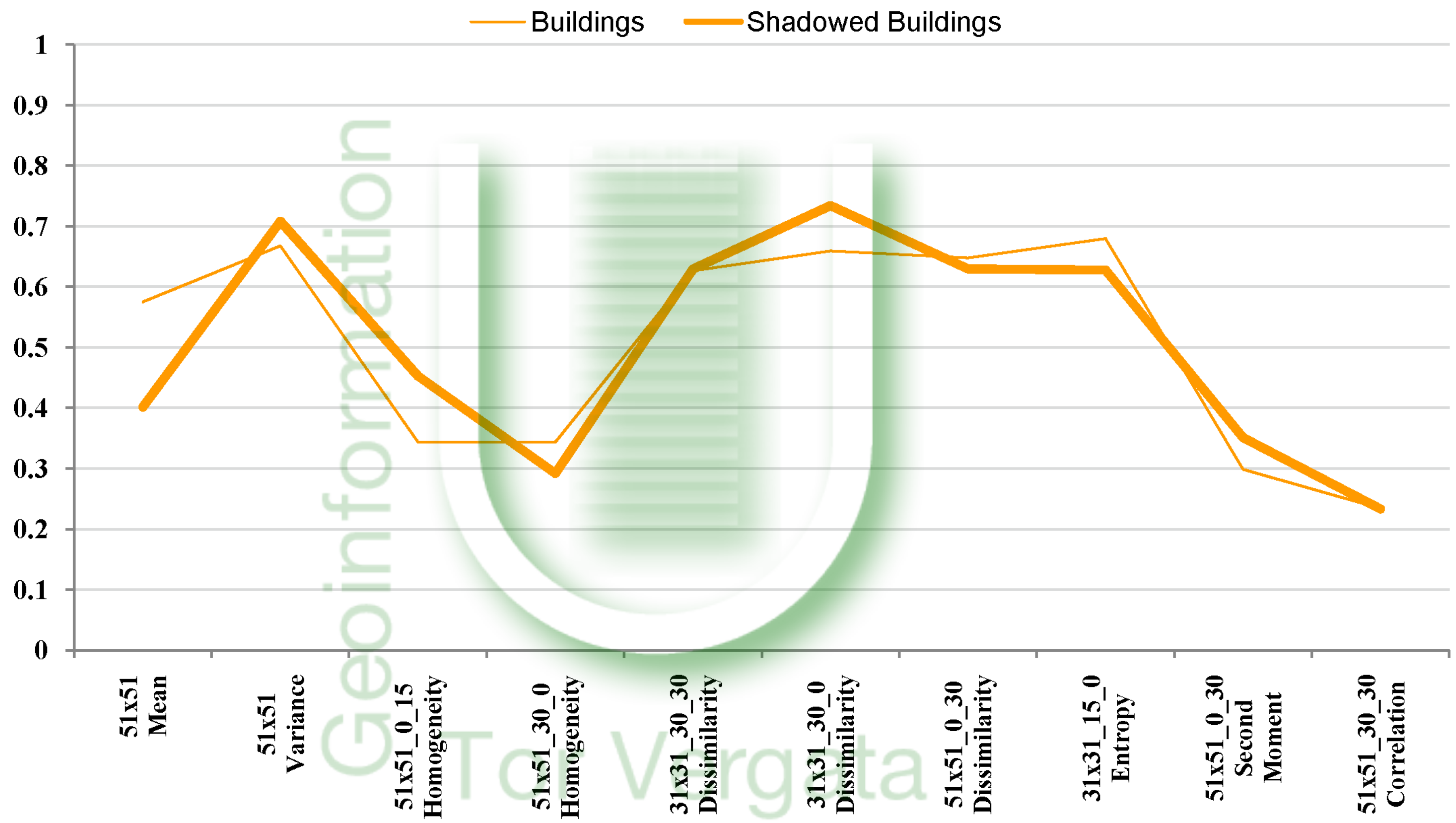
***k*-Coeff. = 0.224**

Textural Analysis – shadowed areas of the Rome set

	Bare Soil
	Apartment Blocks
	Buildings
	Railway
	Roads
	Soil
	Tower
	Trees
	Short Vegetation



Textural Analysis – shadowed areas of the Rome set



Conclusions

A **multi-scale textural** approach made it possible to classify urban LAND-USE on a **per-pixel** basis overcoming the spectral information deficit of panchromatic imagery.

The obtained classification maps not only showed different asphalt surfaces, such as **ROADS**, **HIGHWAYS** and **PARKING LOTS**, but also discriminated traffic patterns in the parking lots. The method also differentiated building architectures, such as **RESIDENTIAL HOUSES**, **APARTMENT BLOCKS** and **TOWERS**.

The analysis of the feature contributions indicates the importance of using cell dimensions greater than **31x31 pixels** for images with a 50 cm resolution. **Dissimilarity** appears to be the most significant textural feature among those considered.

The ten features selected appear to generalize well to new urban scenes.

Shadowed areas show their own texture properties with respect to non-shadowed areas of the same class.

Thank you for your attention!

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