Hydrological modelling via aerial image segmentation

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Collaborator credits

- Roland Burkhard – Heriot-Watt University
- Andres de Moran – Madrid
- Tak Chan – City University, Hong Kong

Related publications

- IEEE ICIP 2009, Robertson & Chan
- AGILE 09, Robertson, de Moran, Burkhard, Chan

Objectives

Technical objectives

- Connecting images to hydrological modelling
- Provide "first approximation" solution to the real Land Use classification
- Which doesn't require lots of training
- Discover how a coarse segmentation of remotely-sensed images impacts the surface water flow estimate

Not to solve image segmentation

Social objectives

- Automatic flood risk analysis
- Flooding has greater consequences in poor regions
- GIS metadata requires labelling
- Lack of trained manpower and resources for manual labelling

Toolkit for Developing nations

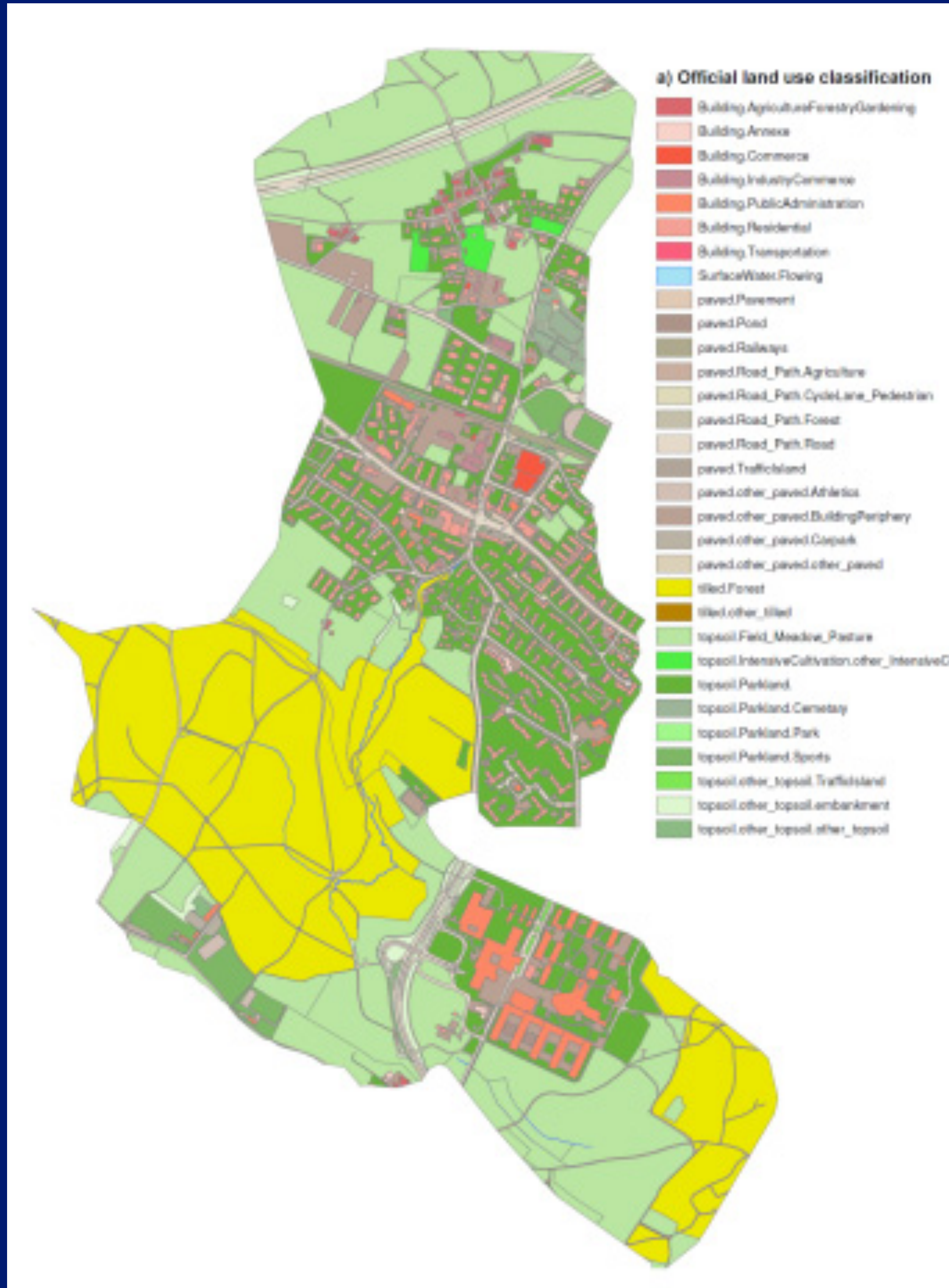
Data

City of Zurich dataset

- 4000 x 4000 pixels
- 200 tiles in the test dataset
- 5 classes drawn from original 34
- Holderbach catchment

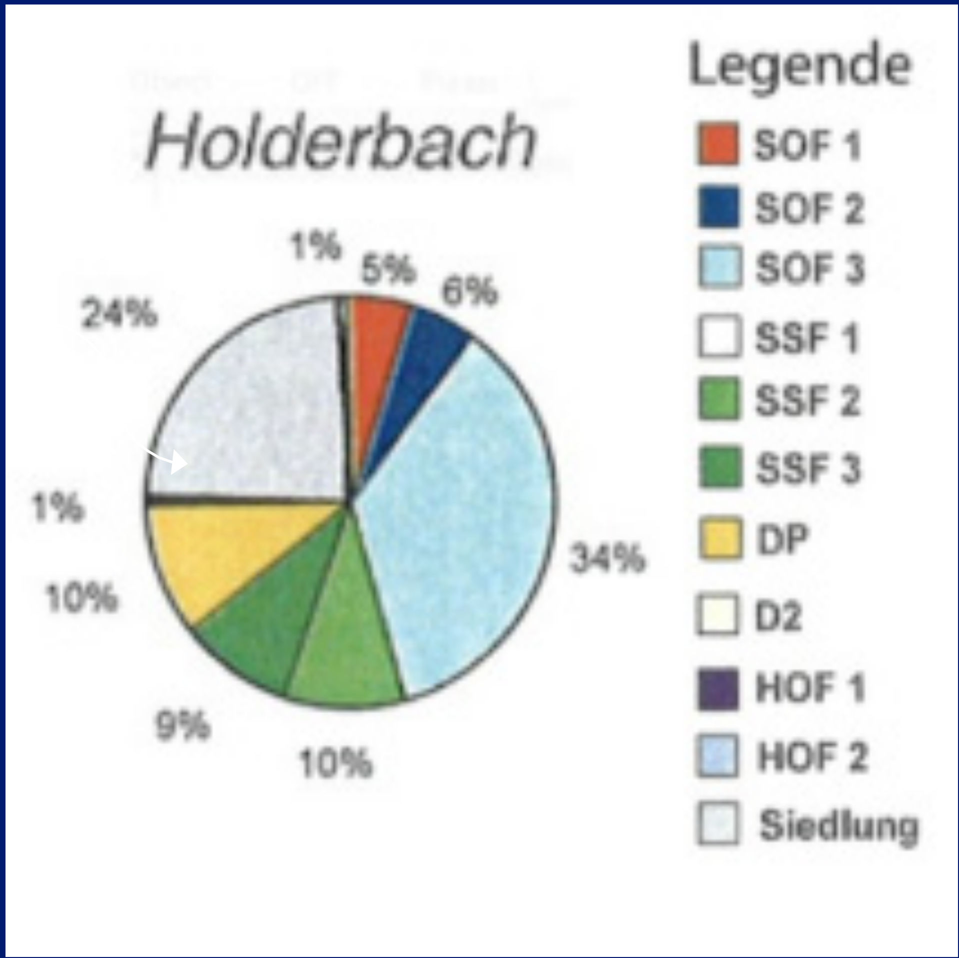
Official Land Use

- Highly detailed
- Labour intensive
- Classes relate to social use of area …
- … not to areas visibly distinct



Holderbach catchment

- Has a significant flood risk
- Highly delayed overland rainfall run-off
- Physical areas are assigned run-off coefficients
- Physical areas linked to GIS cells
- These are the input to model



Run-off coeff (by %)

The classes for segmentation

Can not detect same level of detail as official land use and achieve technical objectives …

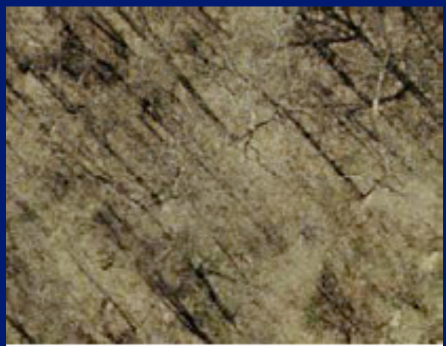
Detailed	Simplified
Building.AgricultureForestryGardening	5-Building
Building.Annexe	
Building.Commerce	
Building.HotelRestaurant	
Building.IndustryCommerce	
Building.PublicAdministration	
Building.Residential	
Building.Transportation	
paved.other_paved.Athletics	4-Paved
paved.other_paved.BuildingPeriphery	
paved.other_paved.Carpark	
paved.other_paved.other_paved	
paved.Pavement	
paved.Pond	
paved.Railways	

The classes for segmentation

Building

Forest

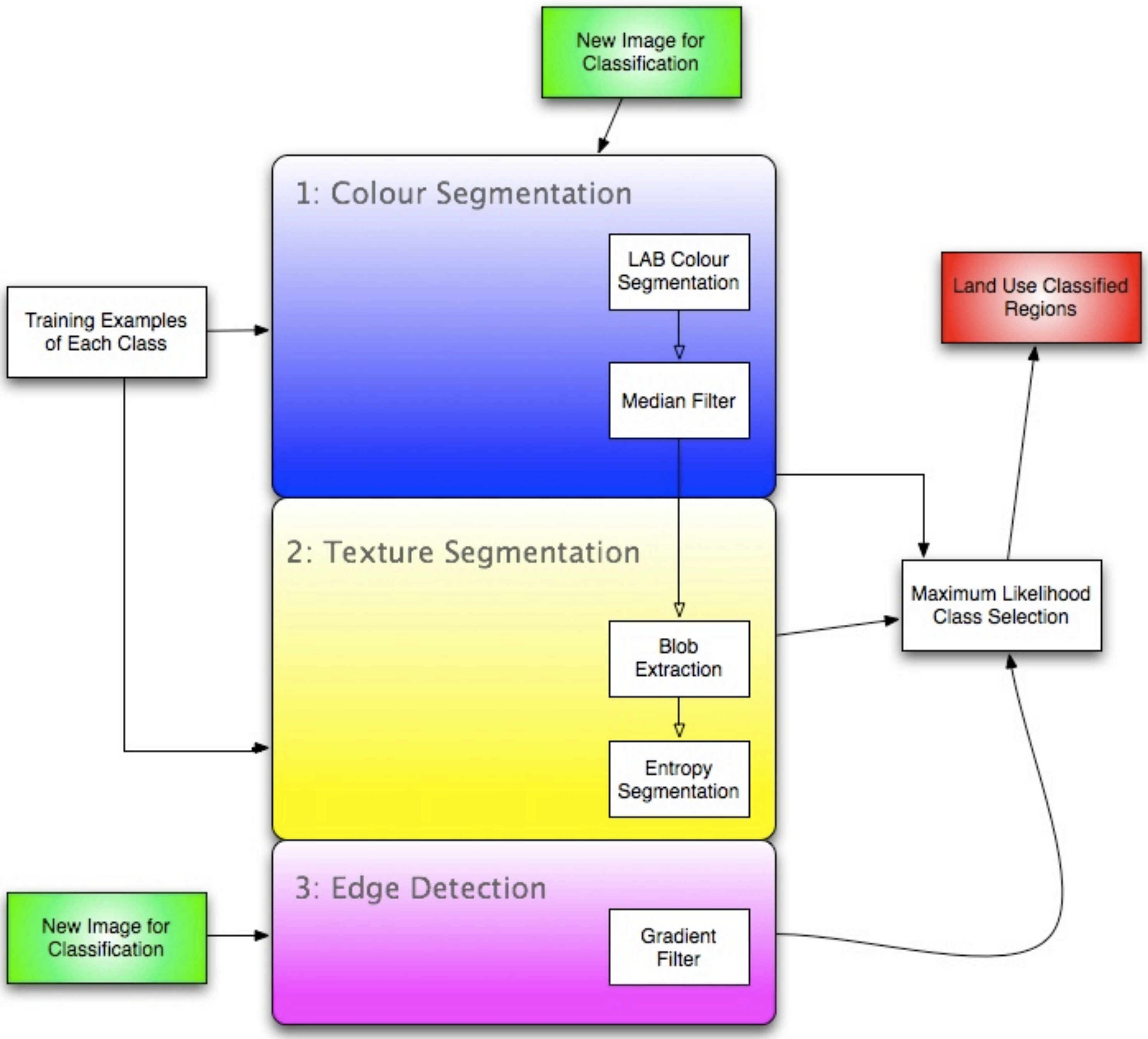
Grass



Topsoil

Paved

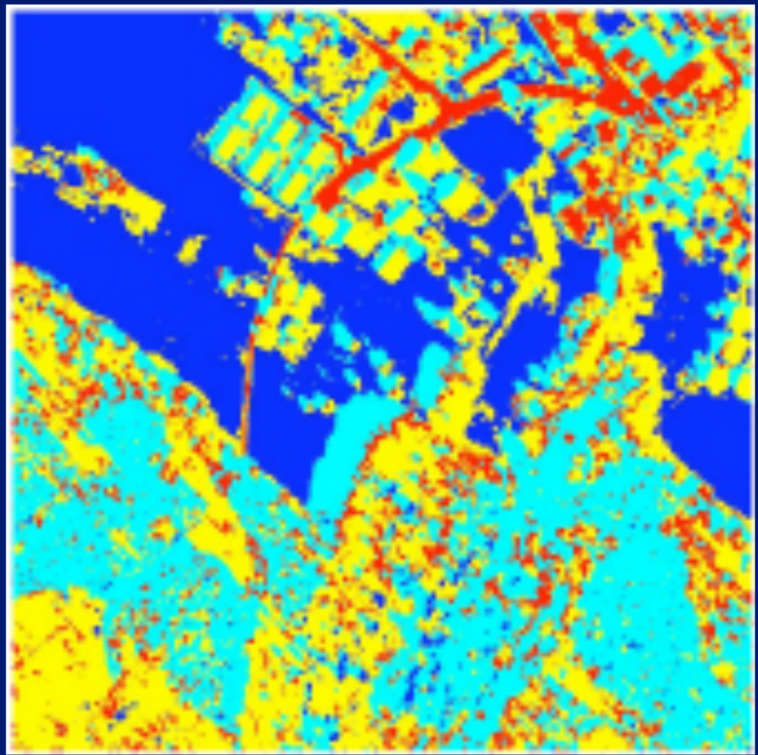
Segmenting Aerial Images



New Image for Classification
1: Colour Segmentation
LAB Colour Segmentation
Median Filter
Training Examples of Each Class
Land Use Classified Regions
2: Texture Segmentation
Blob Extraction
Entropy Segmentation
Maximum Likelihood Class Selection
3: Edge Detection
Gradient Filter
New Image for Classification

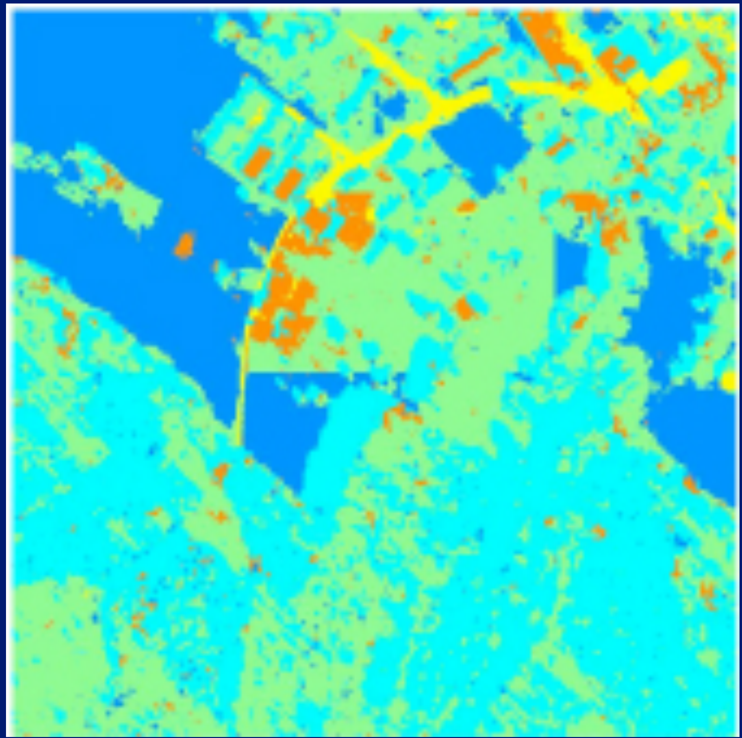
Colour

- Assume given classes are definitive
- Convert to LAB colour
- Compute “distance” from each pixel to each class
- Smooth locally with median filter



Entropy

- Use initial colour results as input -> patches
- Compute local entropy given each patch
- Compute “distance” from each patch to each class



Simple ML estimator

- Compute distribution for each pixel over each class and feature

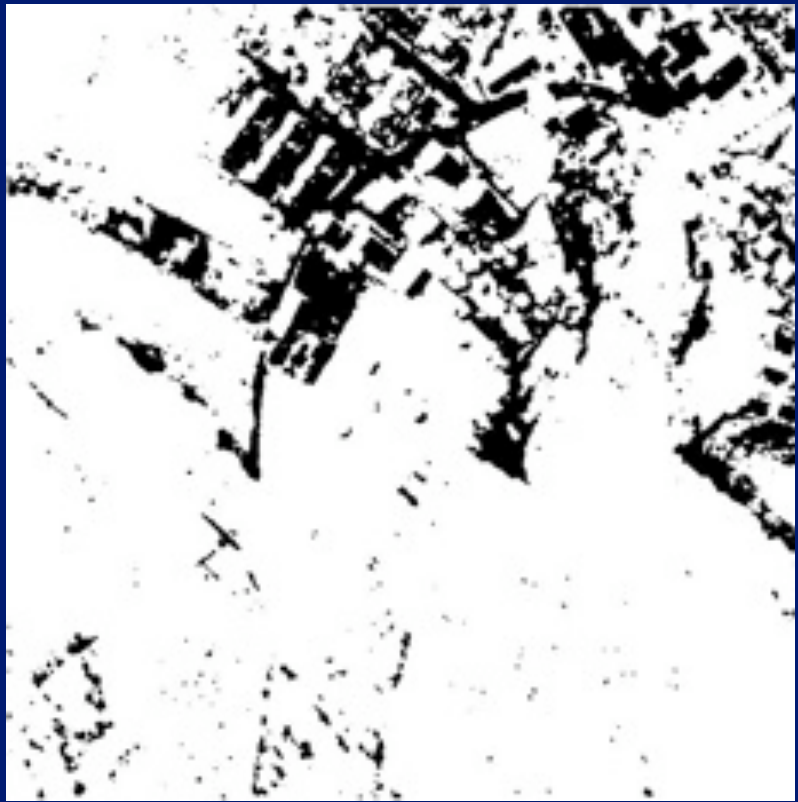
$$p_{ij}^{f}(c|d_{ij})$$

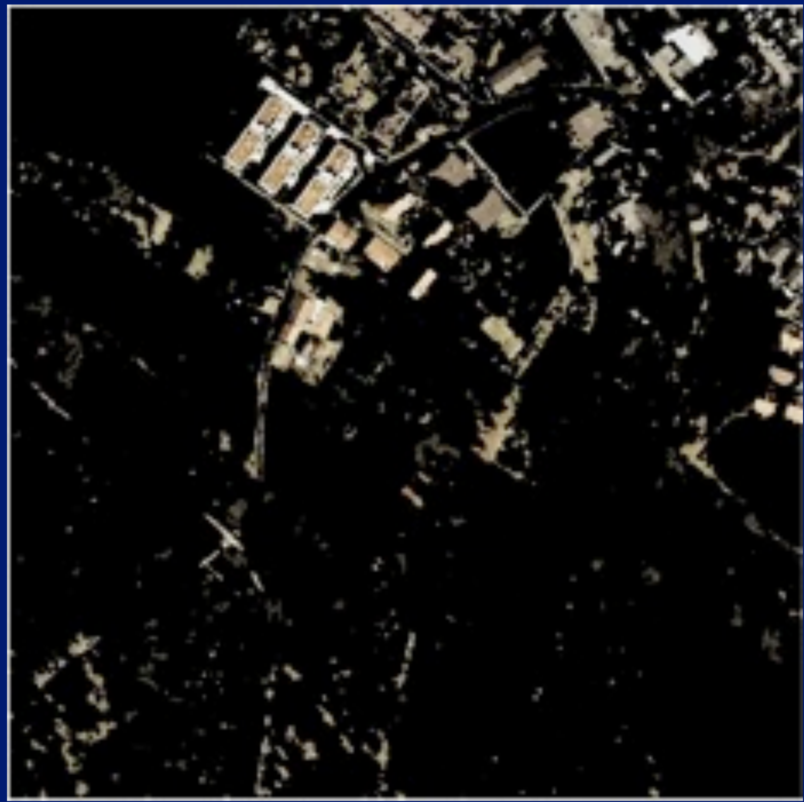
- Currently use 2 features …
- General scheme: weight the distributions

$$C_{ij} = \operatorname{argmax} \prod_{f} p_{ij}^{f}(c|d_{ij})$$

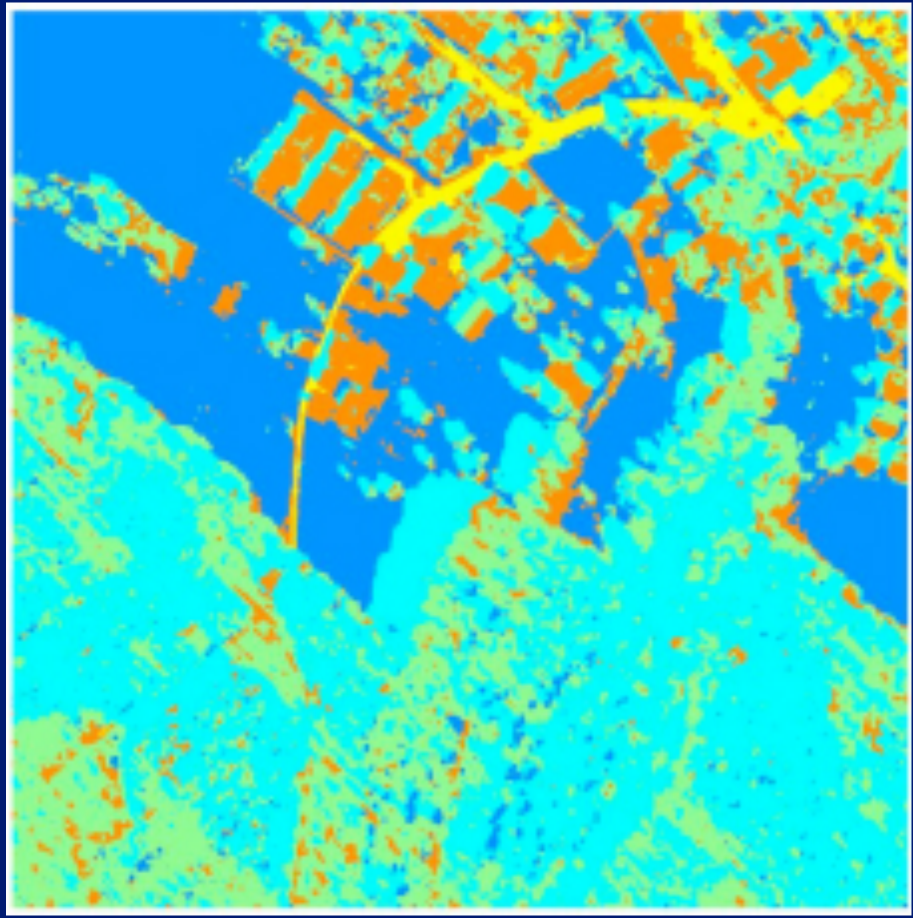
Gradients: minor refinement

- Intra-patch gradient of Grass is large - extract
- Distinguish between Paved & Topsoil at previous stage,
- Remove to leave buildings – heuristic





Final result



How well do we do?

At best, compared to hand-labelled ground truth:

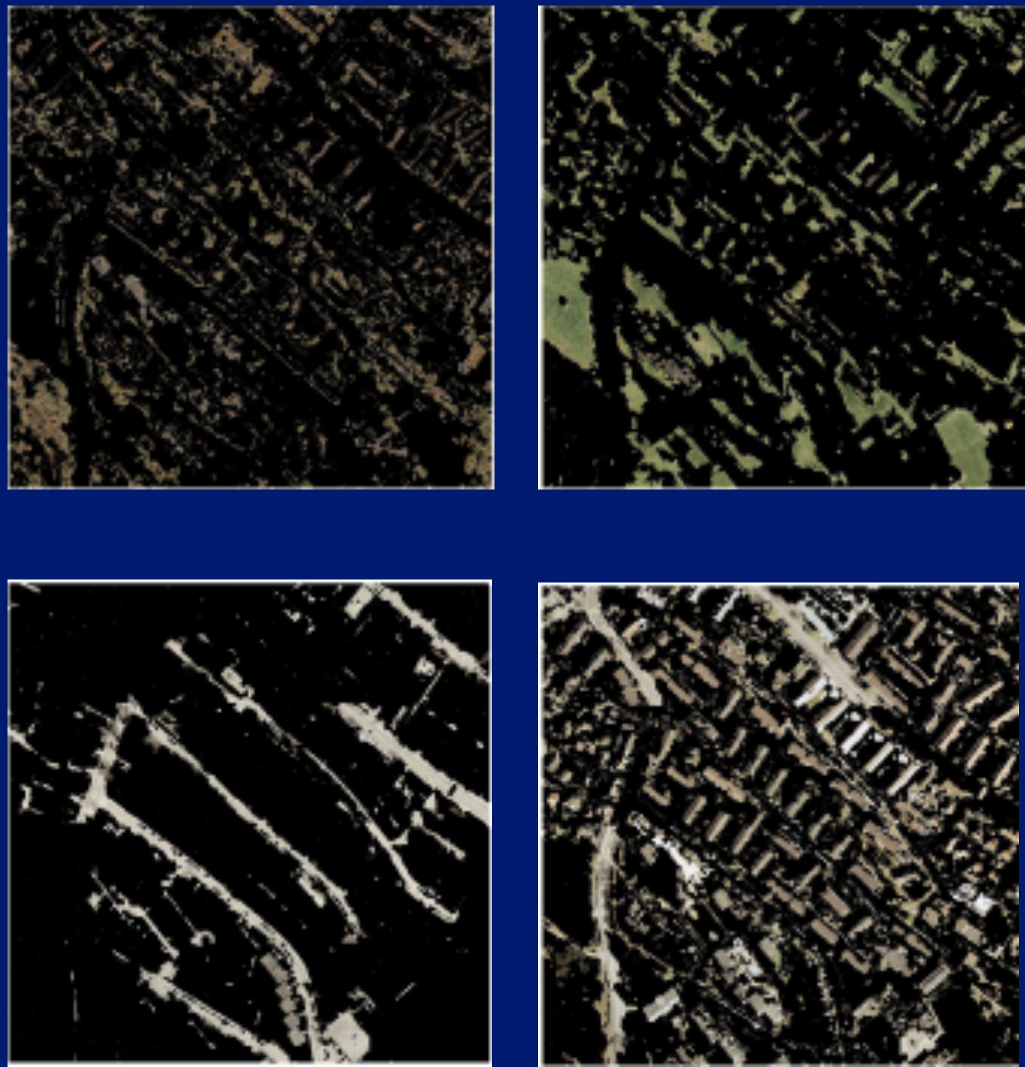
Topsoil	Till	Forest	Paved	Building
80	93	93	56	65

By overall image "type":

Image \ Class	Topsoil	Till	Paved	Building	Total
Mainly Topsoil	63	85	56	60	**66**
Mainly Till	63	89	38	65	**84**
Mainly Urban	64	79	51	63	**62**
Even Distribution	80	93	41	64	**84**

No distinct feature for some classes

Input



Soil

Grass

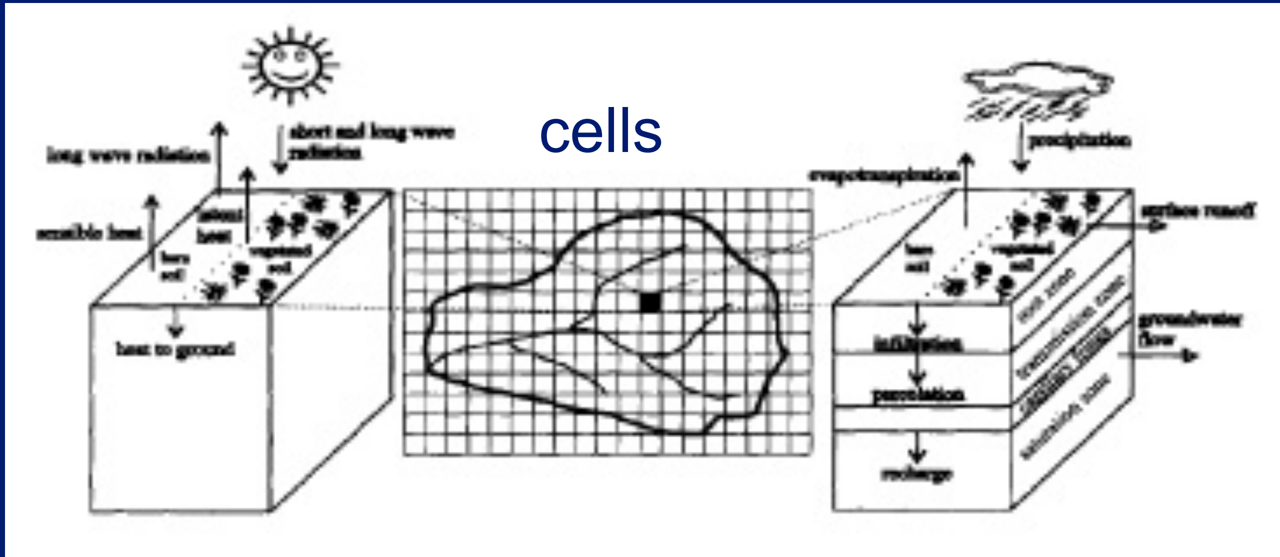
Paved

Building

Hydrological Modelling

Segmentation input to WetSpa

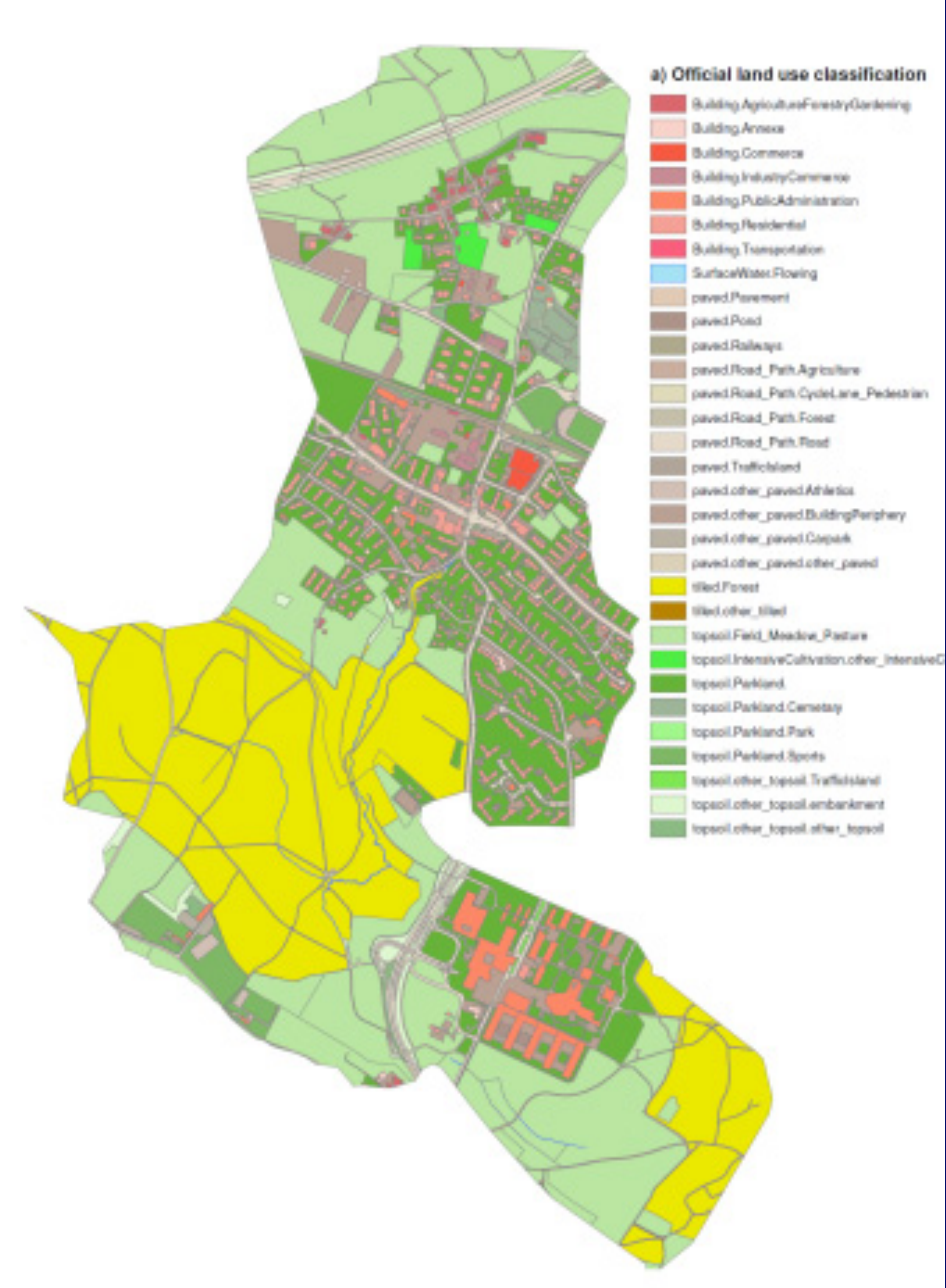
Radiation



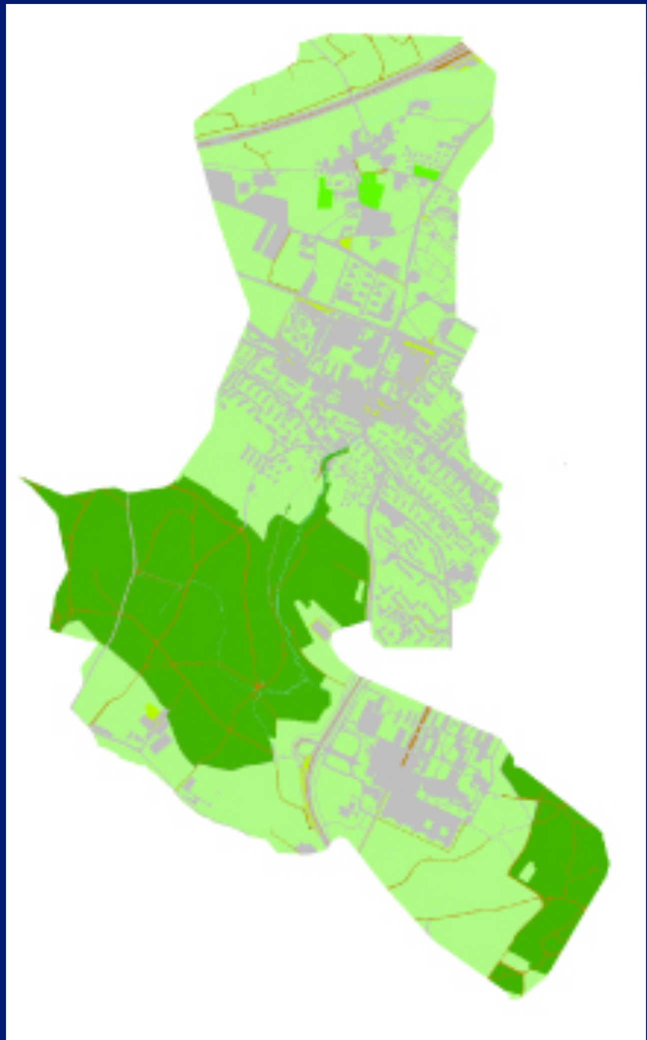
Water

- GIS distributed catchment model (Wang et al. 1996)
- Predicts water and energy transfer between soil, plants, atmosphere
- Regional level in fixed daily timescale
- Runoff defined in each cell and result computed

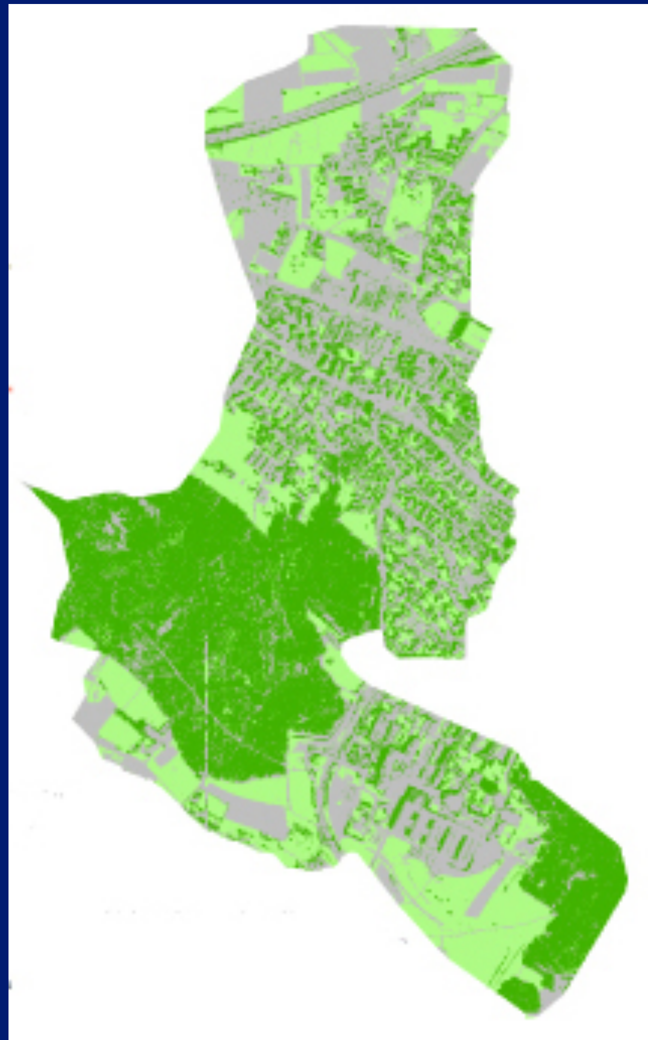
Official Land Use



Reclassification for WetSpa input



Official, reclassified

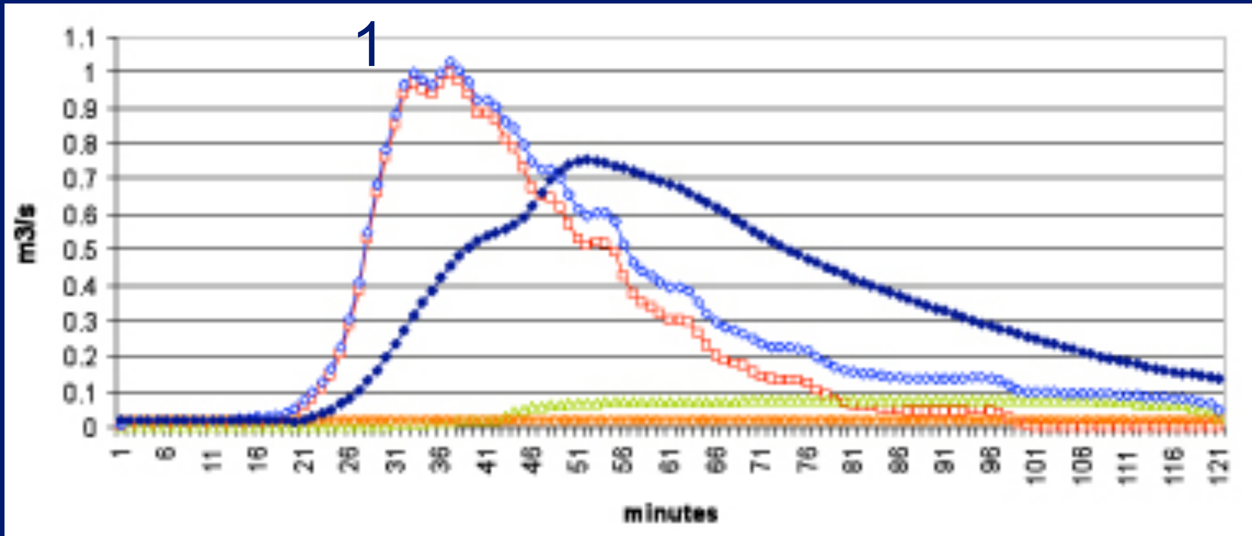


Automatically derived

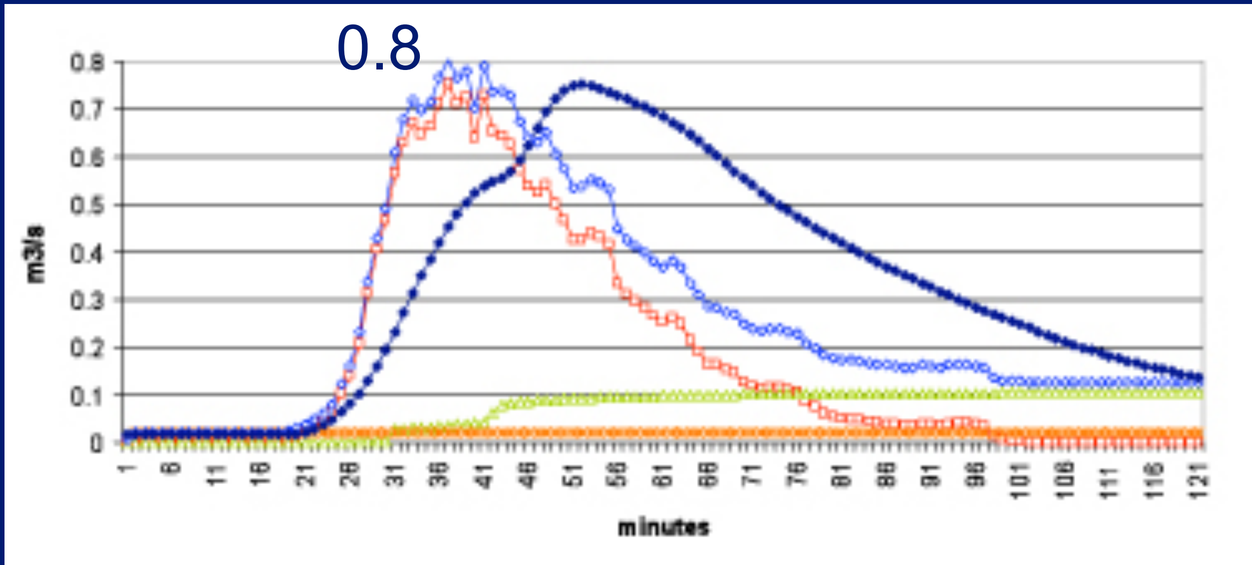
Results

Main peak is

Total flow (m^3/s)



Remotely sensed



“True” flow

Conclusion

Segmentation

- Simple, fast segmentation applied to large dataset
- Minimal training
- Tolerable results compared to hand-labelled data
- Weakness: colour dependent; few features; not fast

Hydrological modelling

- Land use classes can be significantly reduced
- Surprisingly good results using coarse remote sensing
- We overestimate
- Ambiguity between buildings/paved
- They have similar run-off coefficients -> result not affected