Habitat Mapping of an Ikonos Satellite Image Using Kernel-based Reclassification Enhanced with Machine Learning

Andrej Kobler, Slovenian Forestry Institute
Sašo Džeroski, Jožef Stefan Institute
Iphigenia Keramitsoglou, University of Athens

This study was funded by the SPIN project (Spatial Indicators for European Nature Conservation) supported by the European Commission under the Fifth Framework Programme (www.spin-project.org)

Goals of the study

- To examine merits of decision trees to extend the kernel-based reclassification (Barnsley and Barr 1996) to map habitats using a very high resolution satellite image
- Habitat classification of a biodiversity hot-spot in SW Slovenia according to EUNIS nomenclature (EEA 2002)

VHR satellite imagery

- Spatial resolution of satellite imagery improved dramatically since 1972 (Landsat-MSS, 1972 → QuickBird, 2001)
- Gap between available spatial resolution and conventional image classification methods
- Noise in VHR imagery → need to consider also spatial context of the pixel → kernel-based techniques (Haralick et al. 1973)

METHODS – Kernel-based reclassification (KRC) approach

- Originally by Barnsley and Barr (1996) in urban setting
- 2 stages of the KRC algorithm:
  – Initial per-pixel classification (supervised, unsupervised)
  – Reclassification based on class coocurrences / spatial arrangement within square kernel

METHODS – The 2nd stage of the KRC approach (reclassification) – Compute template AEMs

- For each of the reference pixels (i.e. pixels with a known class)
  - Extract the kernel belonging to this pixel
  - Compute an Adjacency Event Matrix (AEM) for each kernel

$$AEM = \begin{bmatrix} f_{11} & f_{12} & \cdots & f_{1n} \\ f_{21} & f_{22} & \cdots & f_{2n} \\ \cdots & f_{ij} & \cdots & \cdots \\ f_{n1} & f_{n2} & \cdots & f_{nn} \end{bmatrix}$$

  - f_{ij} denotes adjacency frequence of classes i and j
- Compute template AEMs for each class

METHODS – Example AEM computation

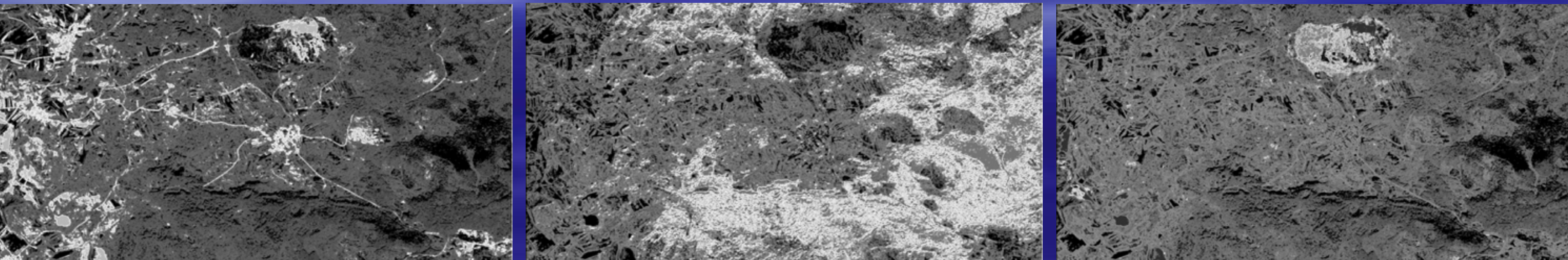
$$K = \begin{bmatrix} A & B & B \\ A & C & B \\ A & C & D \end{bmatrix} \quad \Rightarrow \quad AEM(K) = \begin{bmatrix} 4 & 2 & 5 & 0 \\ 2 & 6 & 4 & 1 \\ 5 & 4 & 2 & 2 \\ 0 & 1 & 2 & 0 \end{bmatrix}$$

METHODS – The 2nd stage of the KRC approach (reclassification) – Compute similarity index values

- For every pixel in the image
  - Get kernel
  - Compute AEM for each kernel

$$\Delta_k = 1 - \sqrt{0.5 N^{-2} \sum_{i=1}^{C} \sum_{i=j}^{C} (AEM_{ij} - T_{kij})^2}$$

  - AEM_{ij} ... element of the AEM
  - Tk_{ij} ... corresponding element of the *template AEM* for class k
  - N ... total number of adjacencies in a kernel
  - C ... Number of output classes
- Result: a set of class-specific similarity images



METHODS – The 2nd stage of the KRC approach (reclassification) – Final reclassification

- Original approach by Barnsley and Barr (1996): assign each pixel to the output class for which Δ_k is maximum
- Our extension of the original approach:
  - assign the output class of each pixel using a decision tree, which reconsiders the whole set of similarity values (Δ_k)
  - use machine learning from examples (Quinlan's See5, www.rulequest.com) to generate the decision tree

METHODS – Classification accuracy

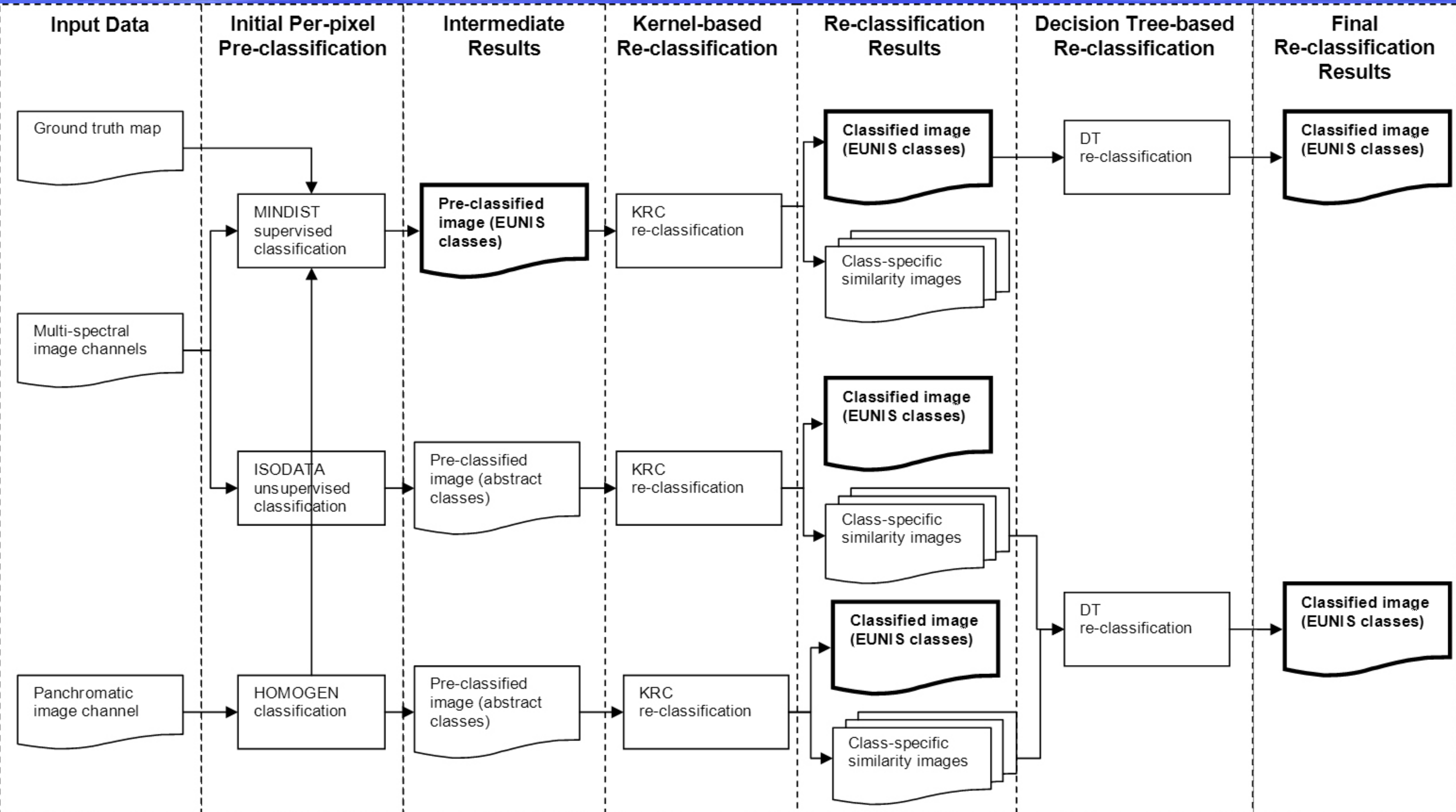
- Kappa statistic (k): indicates the extent to which the correct vaues are due to true agreement vs. chance agreement.

$$k = \frac{observed\_accuracy - chance\_agreement}{1 - chance\_agreement}$$

METHODS – Setup of the study

1. Image data pre-classsification using two per-pixel classification approaches ...
   – unsupervised: ISODATA clustering (→ 10 abstract classes)
   – supervised (used as a baseline approach): minimum distance to nearest class-mean in image channels space (MINDIST) → 10 EUNIS classes
2. ... and a texture based approach
   – panchromatic texture homogeneity image (Haralick et al. 1973) → histogram equalization → 8 discrete homogeneity classes
3. Reclassification using KRC → similarity images (+ classified maps according to original Barnsley-Barr approach)
4. Kernels: 3x3, 5x5, 7x7, 9x9
5. Final decision tree-based reclassification using sets of similarity images (decision trees generated using machine learning from examples)

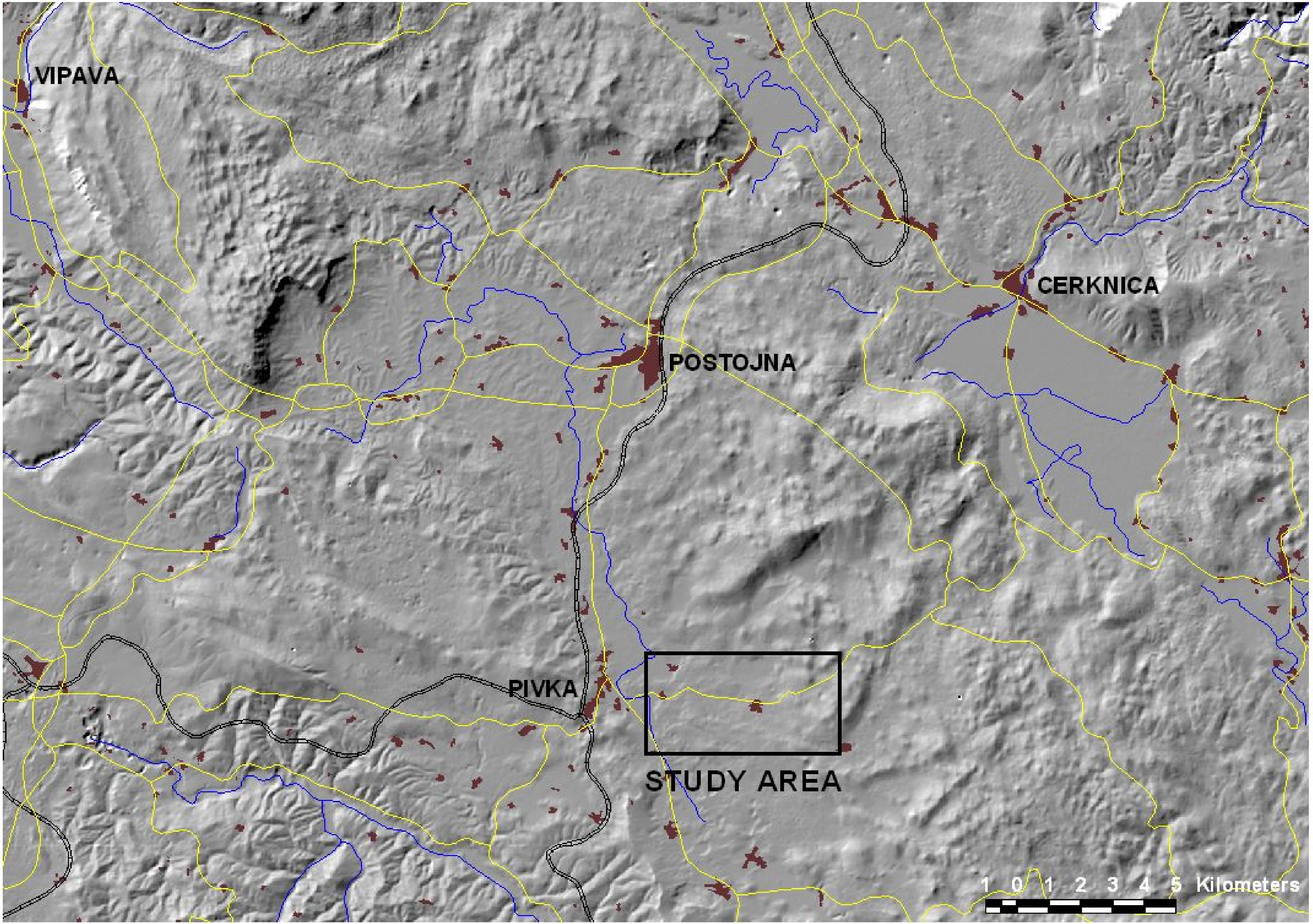
METHODS – Setup of the study



DATA – Study area

- Covers 1952 hectares in SW Slovenia
- Part of a proposed regional park, biodiversity hotspot
- Features grasslands, wetlands, forests

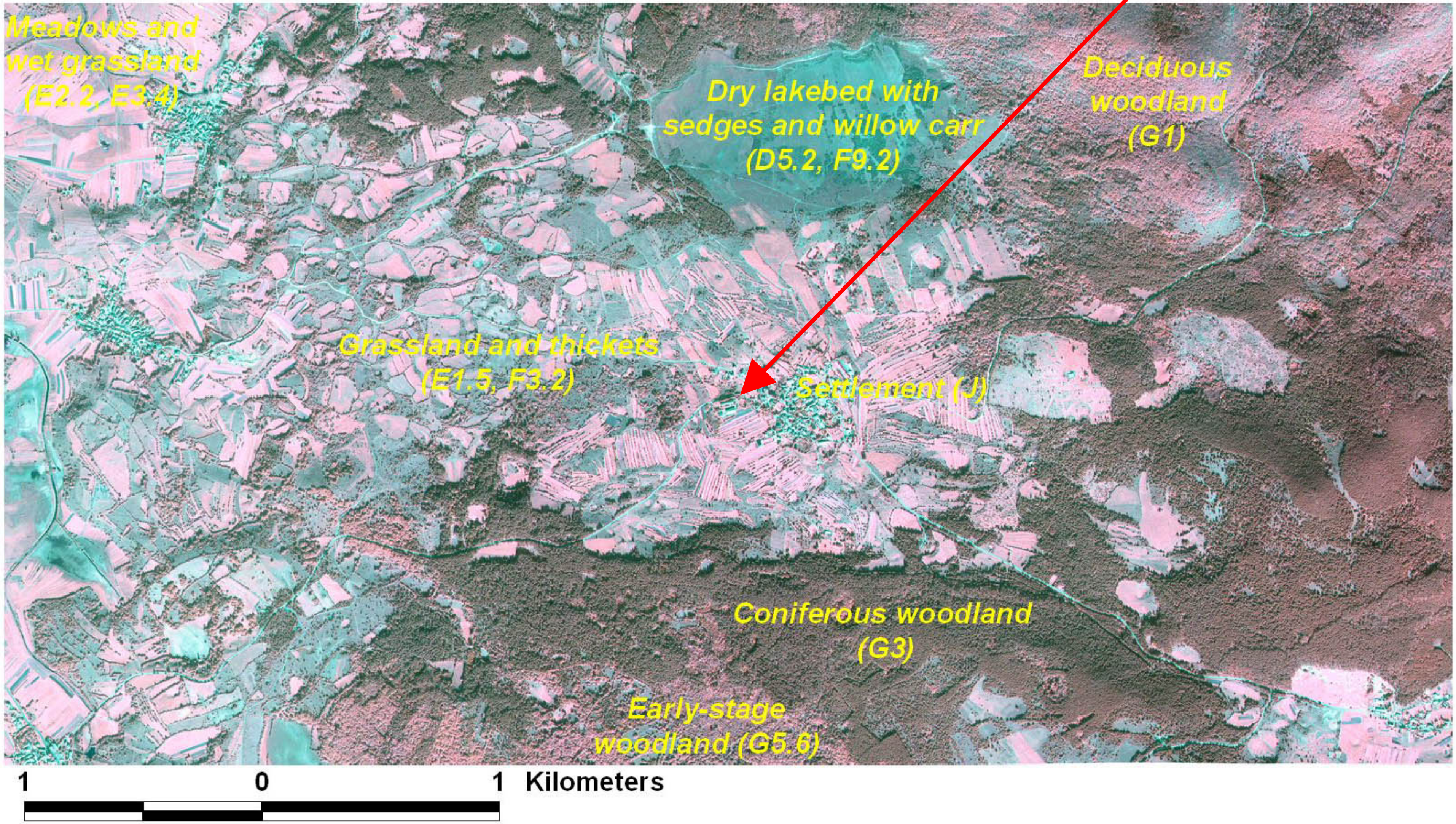
DATA – Study area



DATA – Satellite data

- Ikonos satellite image
  - 1 panchromatic image channel, 1 m spatial resolution
  - 4 multispectral image channels (blue, green, red, IR), 4 m spatial resolution
  - Image acquired on October 14, 2001 (unfavourable date: low sun elevation → long shadows)

DATA – Satellite data

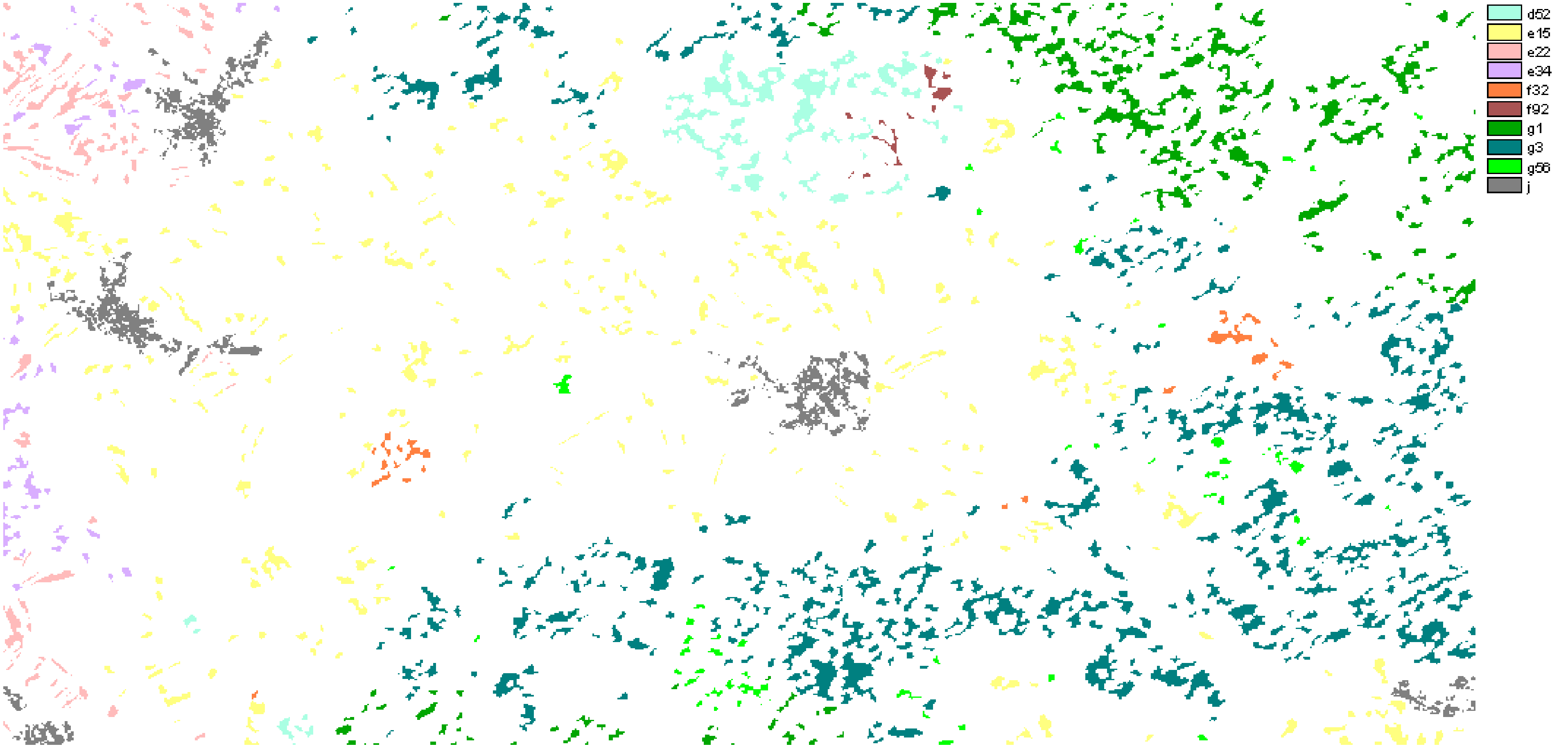


DATA – Ground truth data (EUNIS)

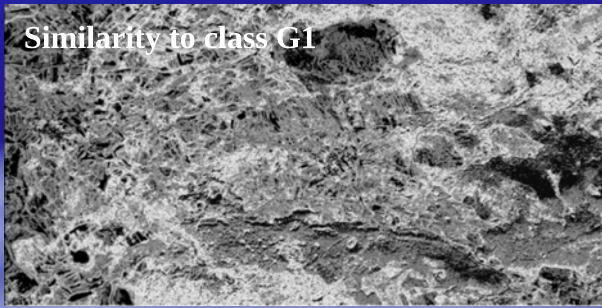
- Consist of 2166 polygons belonging to 10 EUNIS classes
- Polygons were delineated using image segmentation and identified using stereoscopic aerial photo-interpretation
- Only central parts of polygons taken into account to mitigate the boundary effect with kernel algorithm
- A random sample of pixels drawn, distributed into 2 sets (for classification and for accuracy estimation), each containing 380 pixels per class

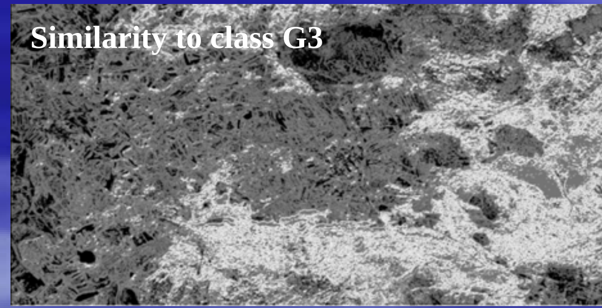
DATA – Ground truth data (EUNIS)

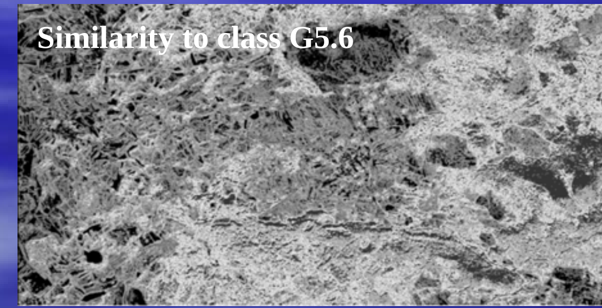
EUNIS code	Description
D5.2	Beds of large sedges normally without free-standing water
E1.5	Mediterraneo-montane grassland
E2.2	Low and medium altitude hay meadows
E3.4	Moist or wet eutrophic and mesotrophic grassland
F3.2	Mediterraneo-montane broadleaved deciduous thickets
F9.2	Willow carr and fen scrub
G1	Broadleaved deciduous woodland
G3	Coniferous woodland
G5.6	Early-stage natural and semi-natural woodlands and regrowth
J	Constructed, industrial and other artificial habitats



RESULTS – Class-specific similarity images (example)







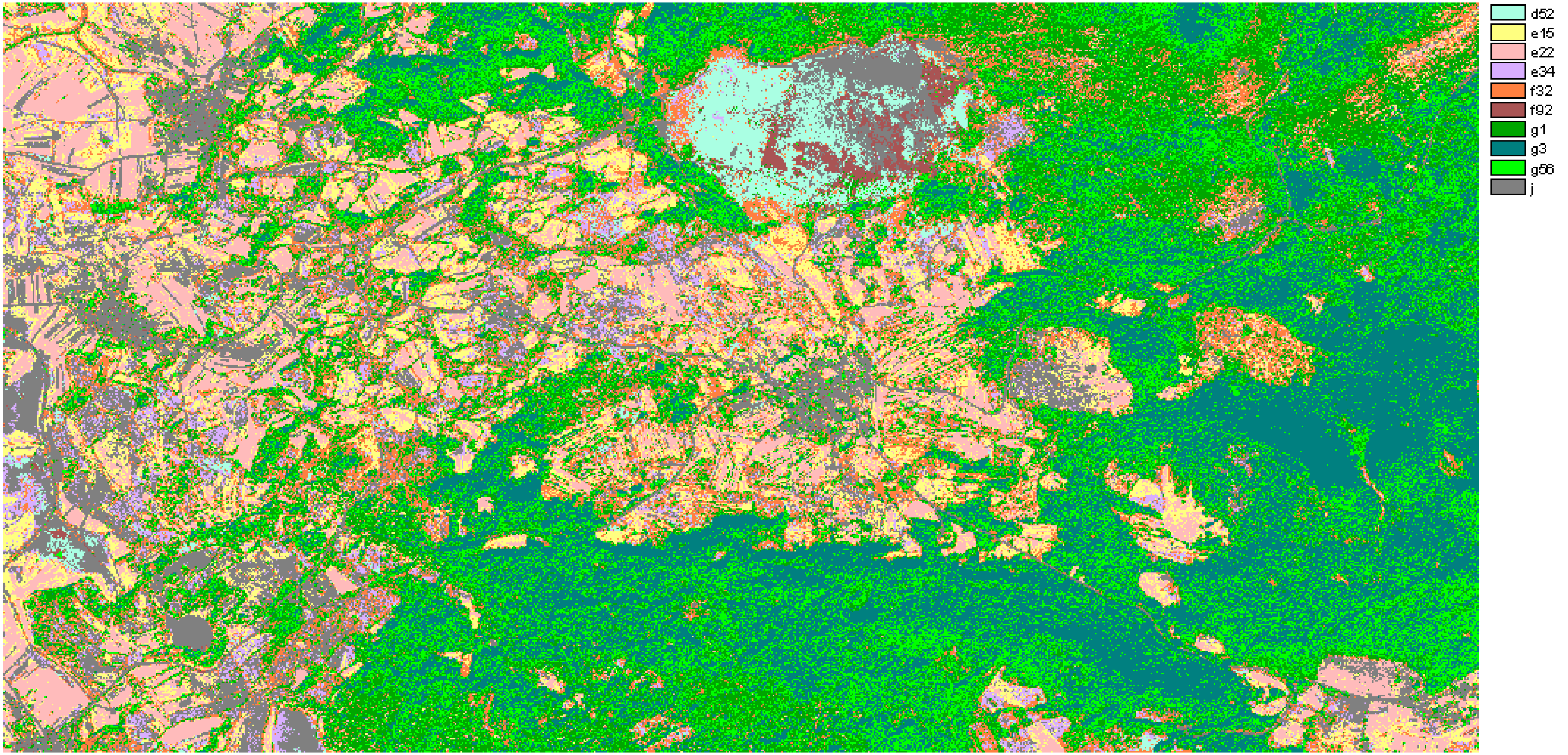
RESULTS – Decision tree

- Example DT
- DT to reclassify combined ISODATA and HOMOGEN based similarity values into EUNIS classes
- Kernel size 7x7

```
See5 INDUCTION SYSTEM [Release 1.10]    Tue May 25 14:17:00 2004
    Options:
        Pruning confidence level 1%
        Test requires two branches with >= 100 items
Read 3955 cases (21 attributes) from homiso_k7.data
Decision tree:
HOMOGEN_similarity2classG56 <= 0.9233:
:...ISODATA_similarity2classF92 > 0.8721:
:   :...HOMOGEN_similarity2classE34 <= 0.9011: F9.2 (358.0/4.0)
:   :   HOMOGEN_similarity2classE34 > 0.9011: D5.2 (100.0/48.0)
:   ISODATA_similarity2classF92 <= 0.8721:
:   :...ISODATA_similarity2classE22 <= 0.8505:
:       :...ISODATA_similarity2classD52 <= 0.8605: E3.4 (292.0/151.0)
:       :   ISODATA_similarity2classD52 > 0.8605: D5.2 (432.0/122.0)
:       ISODATA_similarity2classE22 > 0.8505:
:       :...HOMOGEN_similarity2classD52 <= 0.8566: E2.2 (241.0/73.0)
:           HOMOGEN_similarity2classD52 > 0.8566:
:           :...HOMOGEN_similarity2classF92 > 0.9142: F3.2 (155.0/92.0)
:               HOMOGEN_similarity2classF92 <= 0.9142:
:               :...ISODATA_similarity2classE34 > 0.9093: E3.4 (134.0/63.0)
:                   ISODATA_similarity2classE34 <= 0.9093:
:                   :...HOMOGEN_similarity2classG56 <= 0.8959: E1.5 (161.0/71.0)
:                       HOMOGEN_similarity2classG56 > 0.8959: E2.2 (100.0/50.0)
HOMOGEN_similarity2classG56 > 0.9233:
:...ISODATA_similarity2classJ > 0.9285: J (397.0/36.0)
    ISODATA_similarity2classJ <= 0.9285:
    :...ISODATA_similarity2classG3 <= 0.9315:
        :...ISODATA_similarity2classG1 > 0.9393: G1 (299.0/85.0)
        :   ISODATA_similarity2classG1 <= 0.9393:
        :   :...ISODATA_similarity2classD52 <= 0.8478: G3 (148.0/100.0)
        :       ISODATA_similarity2classD52 > 0.8478: F3.2 (367.0/94.0)
        ISODATA_similarity2classG3 > 0.9315:
        :...ISODATA_similarity2classG1 > 0.9459:
            :...ISODATA_similarity2classG3 <= 0.9489: G1 (132.0/64.0)
            :   ISODATA_similarity2classG3 > 0.9489: G5.6 (112.0/39.0)
            ISODATA_similarity2classG1 <= 0.9459:
            :...ISODATA_similarity2classG1 <= 0.9165: G3 (103.0/12.0)
                ISODATA_similarity2classG1 > 0.9165:
                :...ISODATA_similarity2classG3 <= 0.9581: G5.6 (101.0/53.0)
                    ISODATA_similarity2classG3 > 0.9581:
                    :...ISODATA_similarity2classD52 <= 0.8584: G3 (111.0/28.0)
                        ISODATA_similarity2classD52 > 0.8584:
                        :...HOMOGEN_similarity2classG1 <= 0.9611: G3 (107.0/47.0)
                            HOMOGEN_similarity2classG1 > 0.9611: G5.6 (105.0/45.0)
```

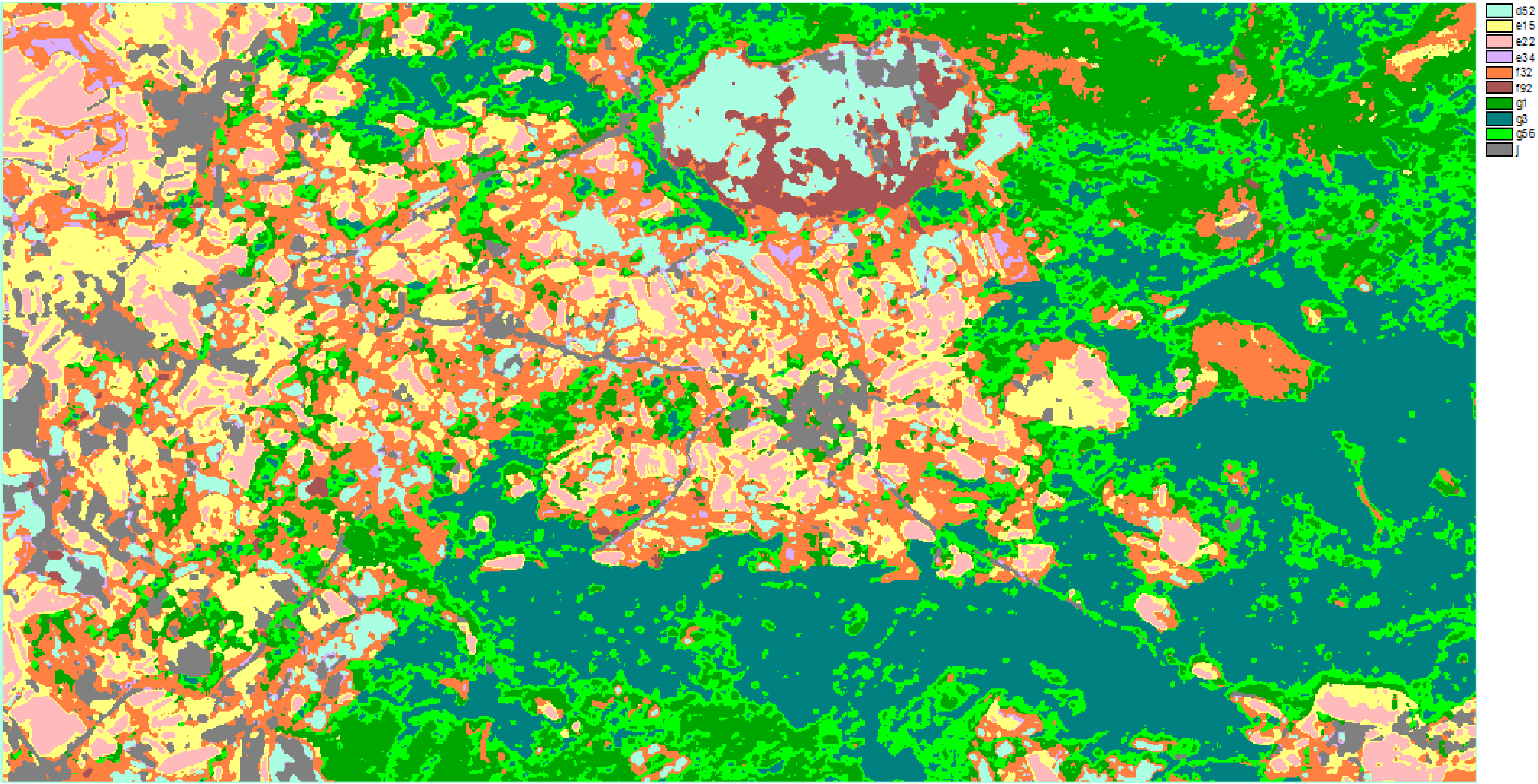
RESULTS – Initial per-pixel MINDIST pre-classification

- Kappa accuracy (10 classes) = 0,48



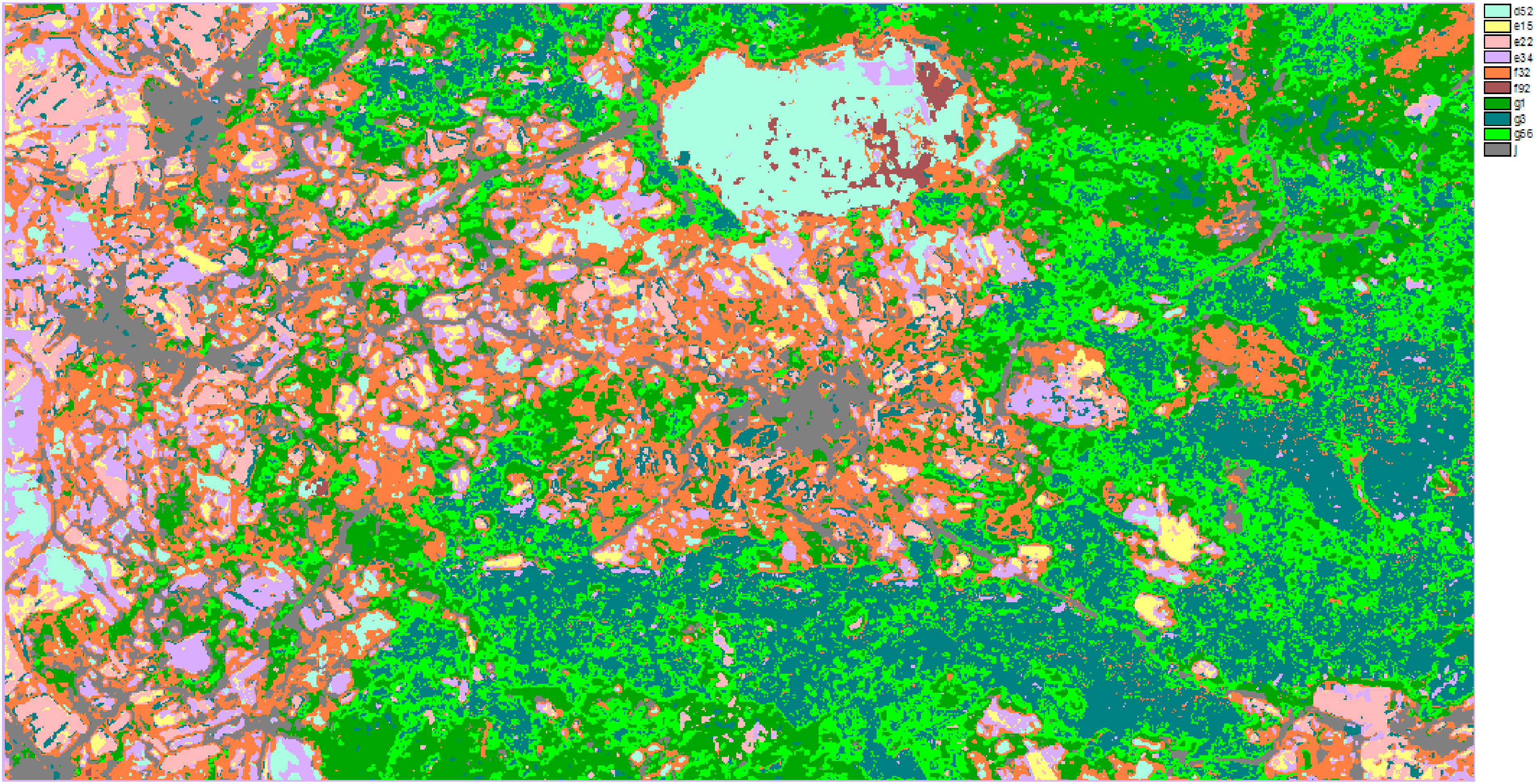
RESULTS – Kernel-based reclassification of ISODATA (original approach)

- Kernel size = 7x7
- Kappa accuracy (10 classes) = 0,56



RESULTS – DT-based reclassification of ISODATA and HOMOGEN similarity images

- Kernel size = 7x7
- Kappa accuracy (10 classes) = 0,60



DISCUSSION – VHR imagery

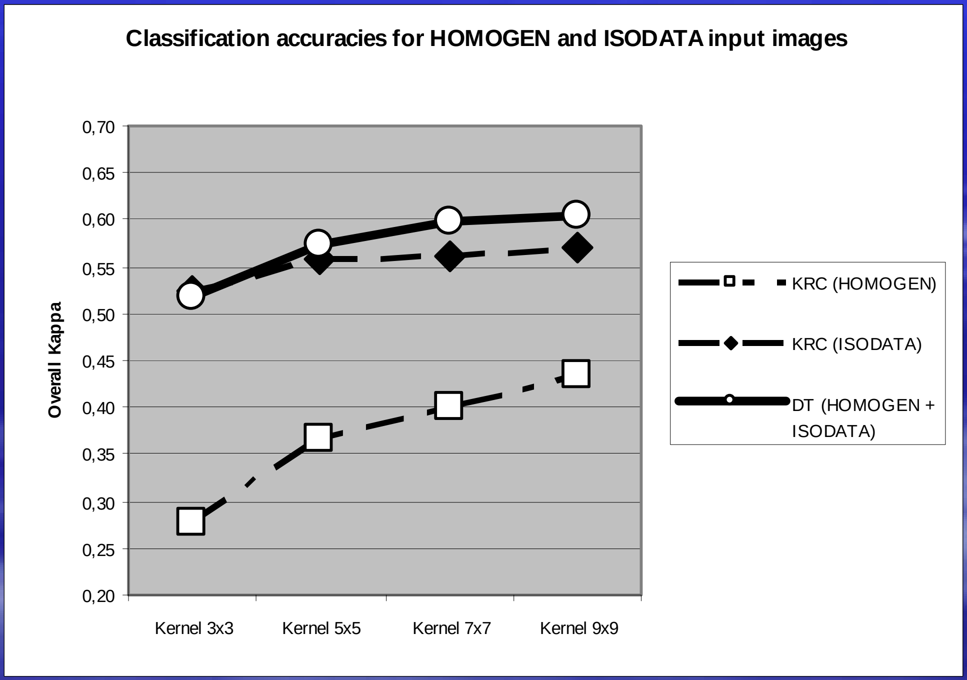
- Spatial context becomes important in VHR imagery when pixel size falls below the size of objects of interest
- Therefore the least accurate is the per-pixel classification due to its inability to consider spatial context

DISCUSSION – Spatial context

- Accuracy is improved by applying any reclassification taking into account spatial context (be it KRC or DT), even with smallest kernel (3x3)
- Tradeoff: loss of spatial detail, inherent to kernel-based algorithms

DISCUSSION – Comparison of reclassification approaches

- Looking at just one kernel size (e.g. 7x7)
- The least accurate is KRC(HOMOGEN) – partly because homogeneity is just one of many possible textural measures (of just one of image channels)
- Followed by KRC(ISODATA) and DT(ISODATA)
- The highest accuracy is achieved by DT(HOMOGEN+ISODATA)



DISCUSSION – Input data

- Merging pre-classified ISODATA and HOMOGEN images to maximize information content before applying KRC?
- NO, because:
  - Merged pre-classified image with large number of classes (e.g. 10x8=80) would yield large AEMs, which is costly to compute
  - Large AEMs necessarily have many 0s (only a limited number of class coocurrence types can be expected) → AEMs statisticaly not significant

DISCUSSION – DT / KRC comparison

- Merging several pre-classified images in the context of KRC is therefore not practical
- However, sets of similarity images resulting from different pre-classified images can be merged using a DT
- The ability to consider more input information is the main advantage of DT over KRC as detected in this study
- Therefore further accuracy improvements are possible using DT approach by incorporating ancillary information (e.g. multi-date satellite imagery, multiple textural measures, thematic GIS layers)

Thank you for your attention