HACC-spatial: Hierarchical Agglomerative Spatially Constrained Clustering

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Precision Agriculture

- GPS technology used in site-specific, sensor-based crop management
- combination of agriculture and information technology
- data-driven approach to agriculture
- lots of data analysis tasks

Data Details – Example Field

Figure: F550 field, depicted on satellite imagery, source: Google Earth

Data Details – Features

- collect a number of geo-coded, high-resolution features such as:
  - N1, N2, N3: nitrogen fertilizer application rates in 2004
  - REIP32, REIP49: vegetation index (red edge inflection point) in 2004
  - Yield: corn yield 2003, winter wheat yield in 2004 and 2007
  - EC25: electrical conductivity of soil in 2004
  - pH, P, K, Mg: soil sampling in 2007
- one field available, 1080 records in $25 \times 25m$-resolution on a hexagonal grid

Data Details – Temporal Aspects

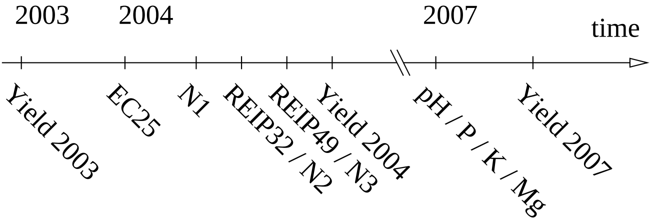
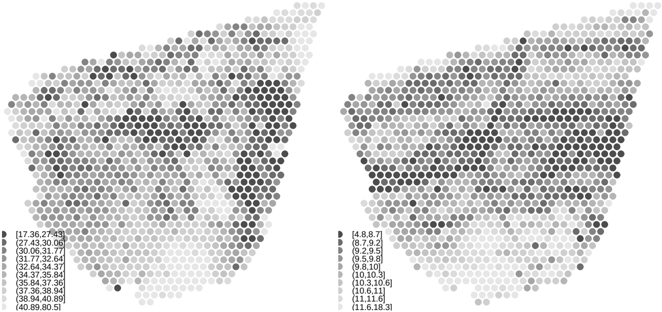


Figure: timeline of data acquisition

Spatial Autocorrelation

Are (spatial) data records independent of each other?

(Do we have spatial autocorrelation?)



(a) EC25 (b) Magnesium content

Figure: F550, EC25 and Magnesium readings

Management Zone Delineation

- A common task in agriculture:
  - subdivide the field into smaller zones
  - zones are rather homogeneous
  - zones are spatially mostly contiguous
  - similarity between zones is low
- $\longrightarrow$ spatial clustering

Literature Approaches

- mostly non-spatial algorithms are used
  - no spatial contiguity
  - small islands, outliers, etc.
  - black-box models
  - fuzzy c-Means, k-Means, etc.
- spatial contiguity is not always required, but desirable
- spatial autocorrelation is usually neglected rather than exploited

Spatial Contiguity Constraint

- spatial clustering = clustering with a spatial contiguity constraint
- $\rightarrow$ constrained clustering
- Keep it simple and understandable:
  - hierarchical clustering
  - agglomerative clustering
- Idea:
  1. (optionally) split field into small zones which are homogeneous
  2. iteratively merge clusters obeying similarity and spatial constraint

Optional Spatial Tessellation

- k-Means clustering on the data points' coordinates
  - due to spatial autocorrelation, adjacent points are likely to be similar
  - this ensures homogeneity of these small zones
  - k is user-controllable and easy to understand
    - homogeneous field: smaller k
    - heterogeneous field: higher k

Optional Spatial Tessellation

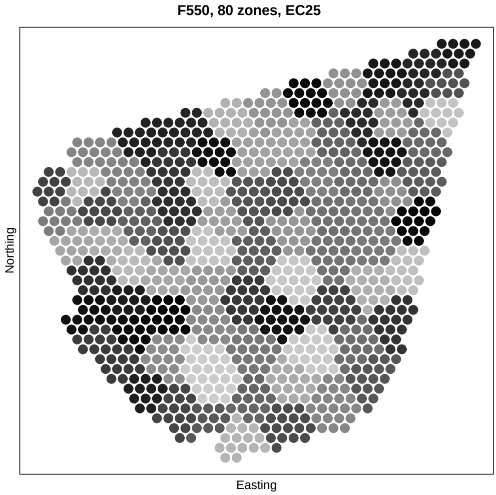
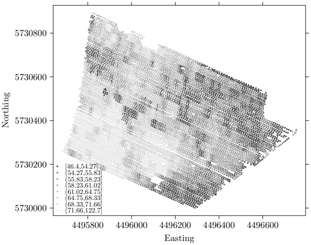


Figure: Tessellation of F550 using k-means, $k = 80$ (grey shades are for illustration only, no further meaning here)

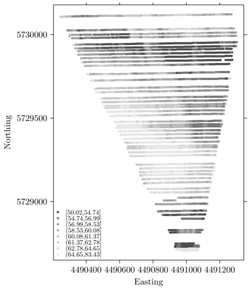
Hierarchical Agglomerative Constrained Clustering

- principle: merge only adjacent objects/clusters, if they are similar enough
  - this ensures spatial contiguity
  - $\rightarrow$ spatial constraint, non-adjacent clusters *cannot link*
- once non-adjacent clusters become much more similar than adjacent ones, they may be merged
  - introduce a user-controllable *contiguity factor cf*
  - $cf \geq 2$: high contiguity
  - $cf \in [1, 2]$: low contiguity
  - $cf \leq 1$: no contiguity

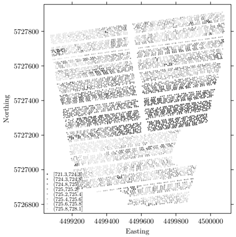
Plots for different predictor variables



(a) F631: EC25



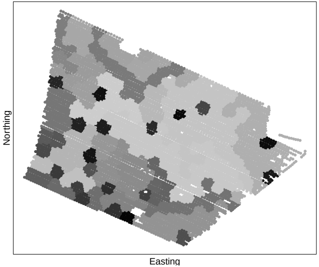
(b) F610: EC25



(c) F440: REIP32

F631, EC25 clustering (low/high spat. contig.)

(a) F631, EC25, 50 clusters

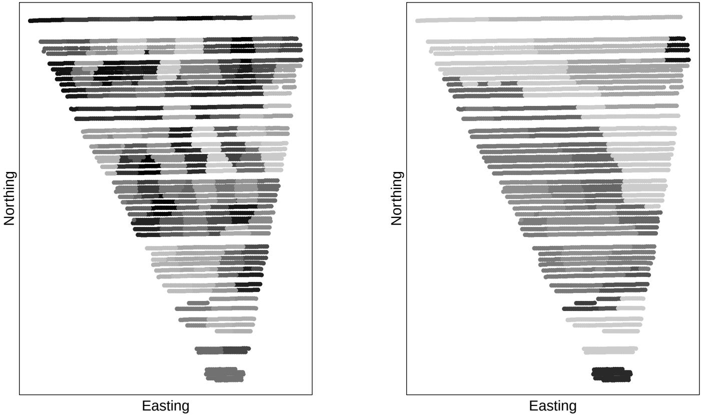


(b) F631, EC25, 50 clusters

(c) F631, EC25, 30 clusters

(d) F631, EC25, 30 clusters

F610, EC25, tolerance against missing data

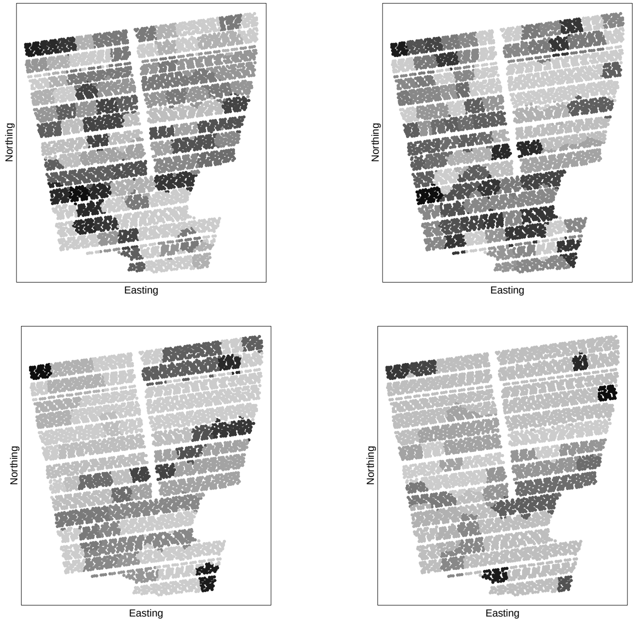


(a) F610, EC25, 100 initial clusters

(b) F610, EC25, 10 zones

Figure: HACC-SPATIAL on F610 using EC25

F440, different contiguity settings (low to high)



Summary

- precision agriculture as a data-driven approach
- spatial, geo-referenced data records in large amounts
- management zone delineation solved as a spatial clustering approach
- important difference between spatial and non-spatial data treatment $\Rightarrow$ use models which are fit for spatial tasks

Time for . . .

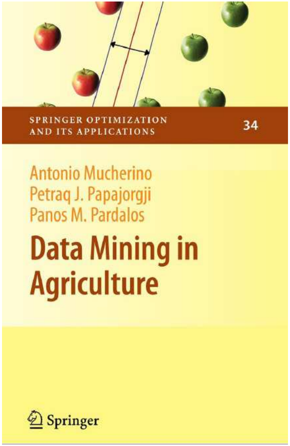
Questions?

Next Workshop *Data Mining in Agriculture* in 2012:
`http://dma-workshop.de`

- contact: `russ@dma-workshop.de`
- slides, R scripts and further info at `http://research.georgruss.de`

Survey on “Data Mining in Agriculture”

- Third paper in this workshop
- by Antonio Mucherino, author of the “Data Mining in Agriculture” book (Springer, 2009)



Survey

- mainly about Antonio's ...
  - biclustering on wine fermentation data
- ... and my work:
  - yield prediction

Wine fermentation

- measure metabolites:
  - glucose
  - fructose
  - organic acids
  - glycerol
  - ethanol ...
- Try to predict problematic fermentations from the above variables
  - cluster known fermentations (normal, slow, stuck), assign score
  - for new fermentations: find best cluster and predict outcome
  - obtain a score for the probability of a fermentation to become problematic

Yield prediction

- collect spatial, high-resolution data
  - vegetation indices
  - fertilizer data
  - previous yields
  - sensor data
  - digital elevation model
- (try to) predict yield
  - regression task
  - use different regression models
  - develop spatial regression
  - as a basis for: assessing a variable's importance for yield prediction
  - $\rightarrow$ spatial variable importance
  - (ongoing part of my PhD thesis)

Other topics

- automatic recognition and grading of fruit (data mining and image processing)
- detection and analysis of animal sounds (data mining and audio signal processing)
- classification of flower species
- estimation of soil properties and soil types
- disease outbreaks, water consumption
- ...