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Mapping the possible occurrence of archaeological finds by Bayesian inference

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- Archaeological prospection & predictive modeling
- Objectives
- Mapping: Bayes: deductive, inductive, mixed model
  Regression indicator kriging
- Precision+accuracy: MBF evidence filter + ROC validation
- Results and conclusions

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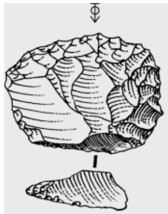
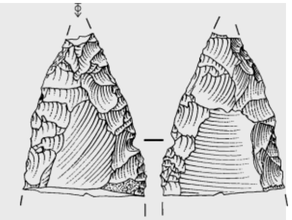


h1,4 - b1,8 cm
98N347HB39a

Archaeological prospection



95N23HB39a h2,7 - b2 cm

- EU Valetta Treaty: protecting the cultural heritage

  Increased need for info on presence, quantity and quality of archaeological heritage → "find databases" with data of various origin:

  1. **Reconnaissance walking**: field loc ±; amateur work; only positives
  2. **Line walking**: scanning line fragments; field loc; common; pos+neg
  3. **Grid walking**: exhaustive; GPS field loc; less common; pos+neg

Predictive modeling

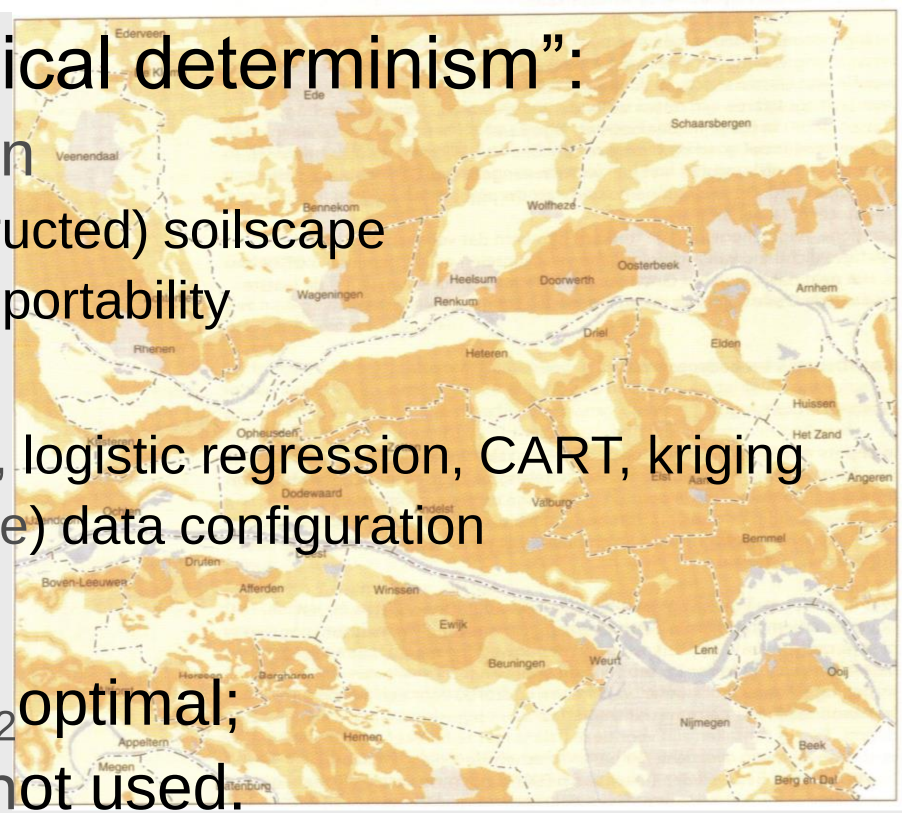
- Two “schools of ecological determinism”:
  - **Deductive**: knowledge-driven

    Most common; based on (reconstructed) soilscape

    Criticism: personal bias, unknown portability
  - **Inductive**: data-driven

    Still few examples; Discr. Analysis, logistic regression, CART, kriging

    Criticism: dependency (unfavorable) data configuration
- Problems:
  - Data configuration often sub$_2$optimal;
  - Information “non-find” often not used.

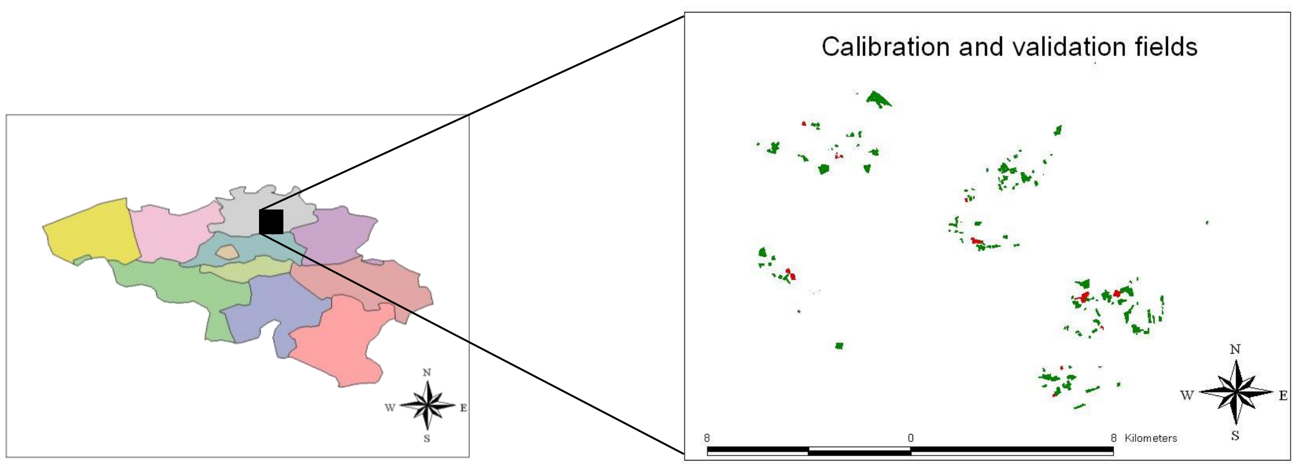


Research Q's + Objectives

1. What mapping method works in difficult data configurations and with + - data?
   - Test potential of Bayesian methods
   - Compare with IRK
   - Compare deductive and inductive methods
2. Political sensitivity: display what (when) on map?
   - Evidence strength filter

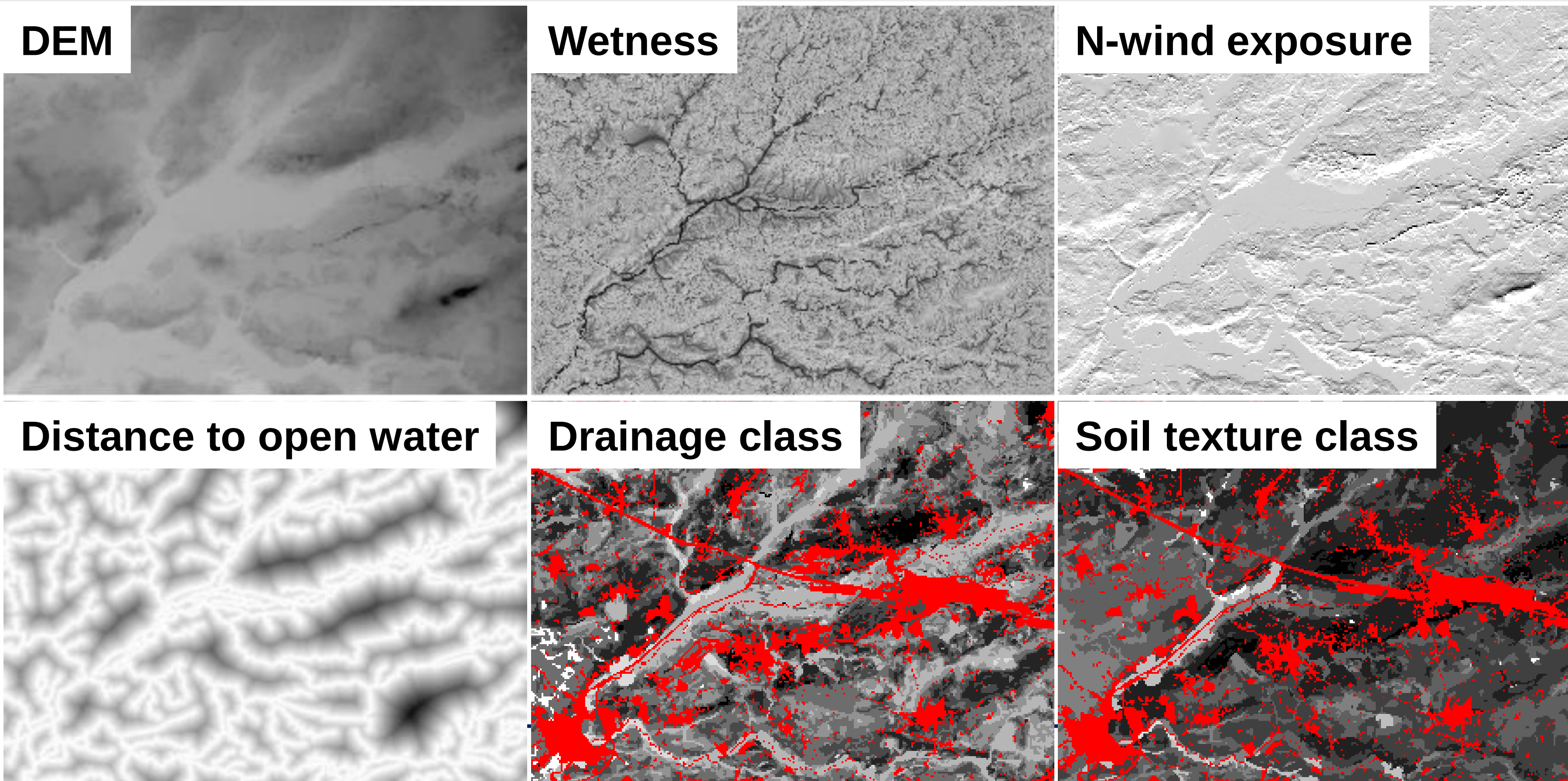
Research area, sampling

- 19x14 km^2 area in N Flanders
- Pleistocene coversand, alluvial plains, tertiary outcrops
- Mostly line walks in threatened (plowed agricultural) fields
- Fields randomly selected (10% sampled area =validation)
- Focus on final-Paleolithic and Mesolithic artifacts
- Finds & non-finds stored in 10x10 m grid (protocol)



Research area: auxiliary variables

- Relevancy for settlement, hunting, gathering



Bayesian mapping

At a location,

1. Prob(occur.|attributes) $$P(o|f) = \frac{P(f|o) \cdot P(o)}{P(f)}$$ (Bayes' rule)
2. CP(attributes) $$P(f|o) = \prod_{i=1}^{n} co_i$$ and $$P(f|a) = \prod_{i=1}^{n} ca_i$$
3. P(attributes) $$P(f) = P(f|o) \cdot P(o) + P(f|a) \cdot P(a)$$

Combination:

(e.g. Aspinall, 1992):

$$P(o|f) = \frac{P(o)\prod_{i=1}^{n} co_i}{P(o)\prod_{i=1}^{n} co_i + P(a)\prod_{i=1}^{n} ca_i}$$

Prior occurrence counted as fraction (occur.+abs.)

CP's individual attributes counted and combined

	DEM1 ca_1	DEM2 ca_2	DEM3 ca_3
Text1 ca_4			
Text2 ca_5			
Text3 ca_6			

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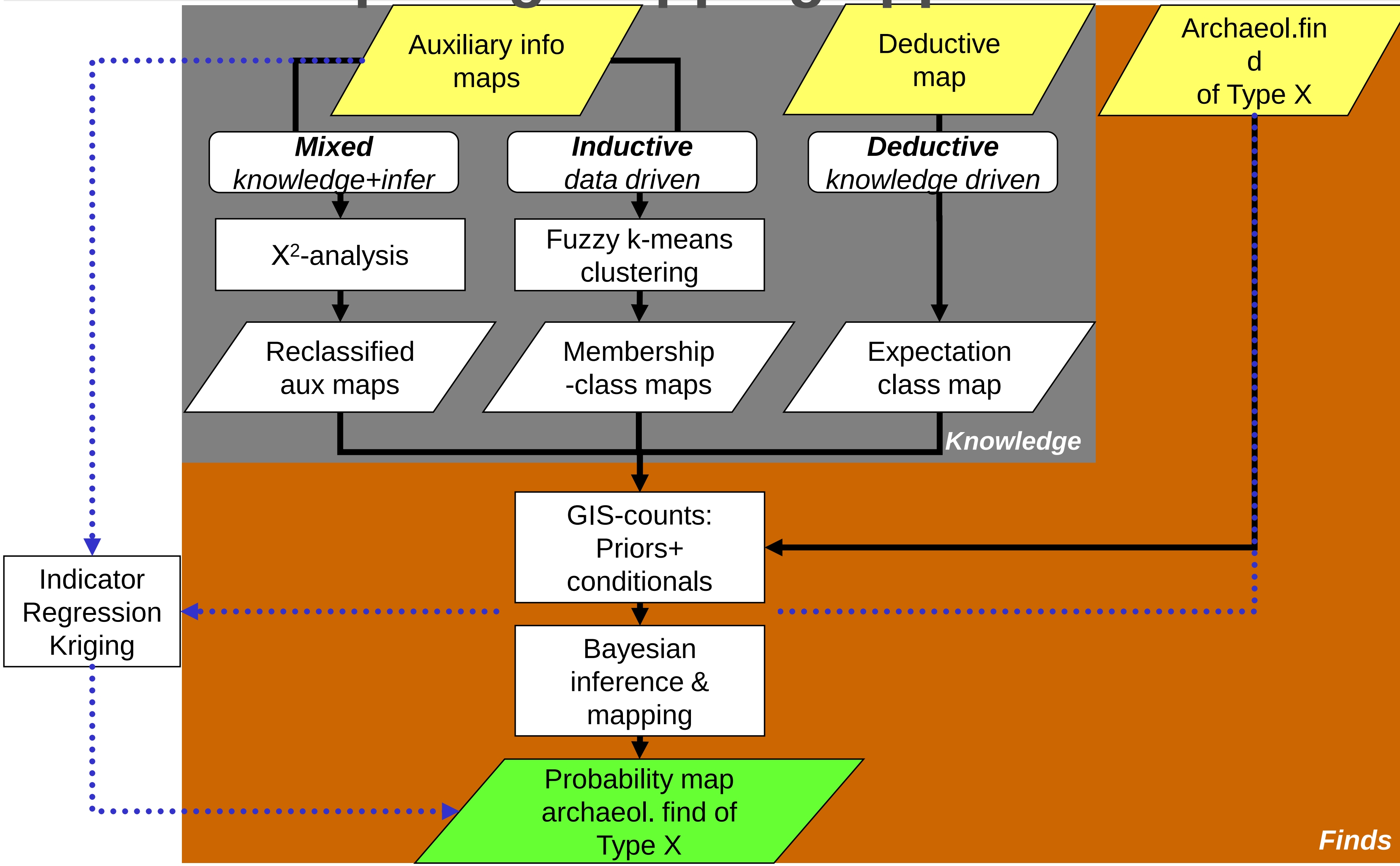
Bayesian mapping (*BayesPMap)*

$$P(o\,|\,f) = \frac{P(o)\prod_{i=1}^{n} co_i}{P(o)\prod_{i=1}^{n} co_i + P(a)\prod_{i=1}^{n} ca_i}$$

1. Deductive method *eqv Aspinall, 1992*
   - *n*=1 (deductive map with m classes)
2. Inductive method *eqv Gorsevski et al., 2003*
   1. Fuzzy *k*-means clustering of auxiliary info (*Matlab-FuzMe*)
   2. *n*=no. clusters, with Σ m membership classes
3. Mixed method *eqv Aspinall, 1992*
   1. Selection of auxiliary information
   2. Supervised classification in classes (distribution + - histogram, χ^2 test) (*interactive software*)
   3. *n*=no. of auxiliary variables; *m* classes

Comparing mapping approaches



Map precision: Evidence filter

Minimum Bayes Factor MBF

(Goodman, 1999): Gaussianity→ $\frac{\Pr(x \mid \mu=\mu,\sigma)}{\Pr(x \mid \mu=x,\sigma)} = \rightarrow\rightarrow \; = e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} = e^{-\frac{1}{2}Z^2}$

***Low MBF=strong evidence against H_0: μ*=prior**

At pixel: *μ*=prior, *x*= P(*o*|*f*), *σ*=? ↓

Bootstrap resampling pos/neg dataset

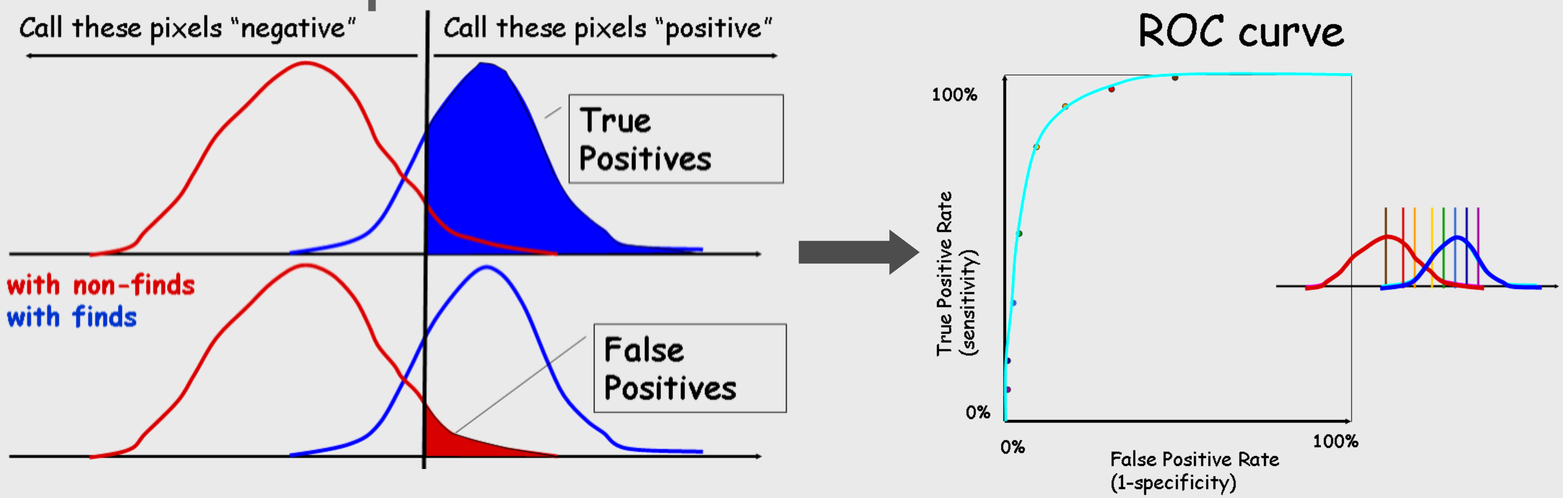
- distribution of CP's → SD_{coi}

1. Error propagation rules
   - SD P(*o*|*f*)
2. Calc MBF per pixel
3. Apply filter for display

P value (*Z*-score)	MBF	Strength of evidence against H_0
0.50 (0.67)	0.79	Absent
0.20 (1.28)	0.44	Very weak
0.10 (1.64)	0.26	Weak
0.05 (1.96)	0.15	Moderate
0.01 (2.58)	0.036	Strong
0.001 (3.28)	0.005	Very strong

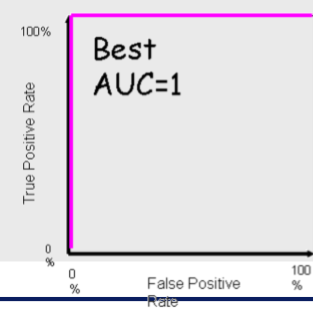
Map accuracy: ROC and AUC

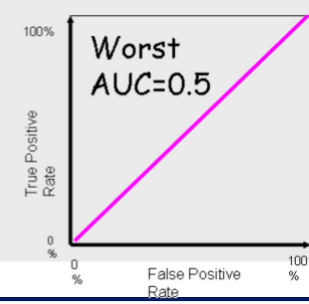
1. Receiver Operator Characteristic



2. Area Under Curve

(eqv. Mann-Whitney *U*)





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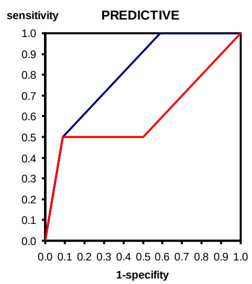
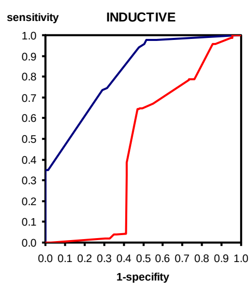
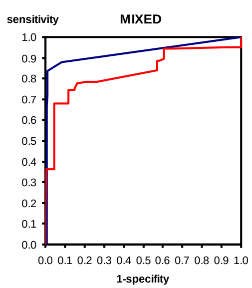
Results: Quality of Bayesian maps

ROC

off   very weak → *evidence filter* → very strong







Predictive
pos+neg

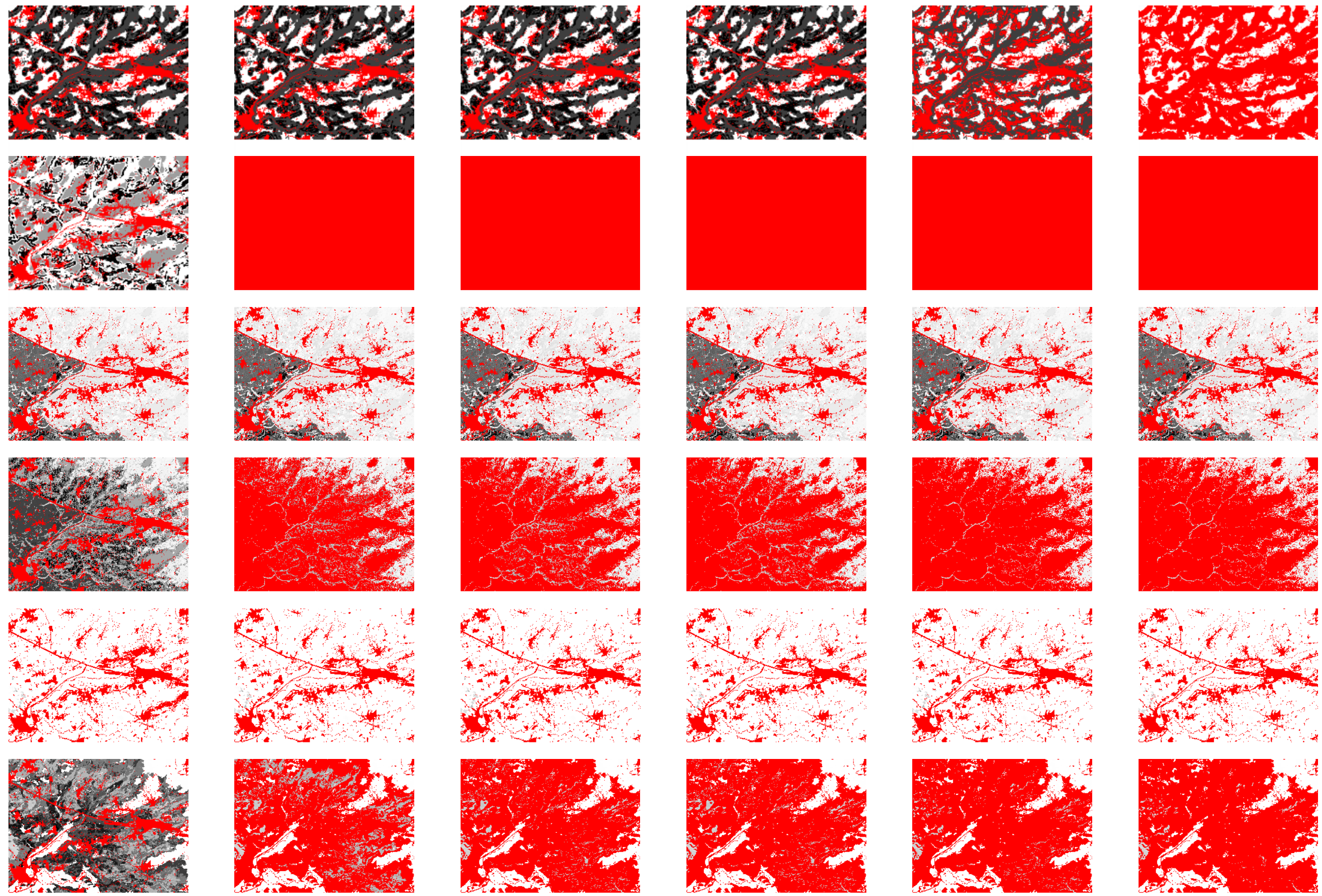
Predictive
pos

Inductive
pos+neg

Inductive
pos

Mixed
pos+neg

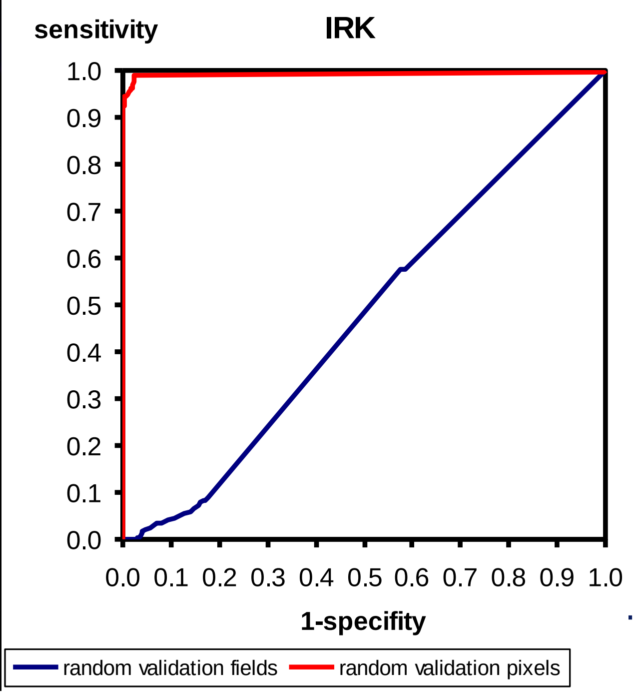
Mixed
pos



Results: comparison with IRK

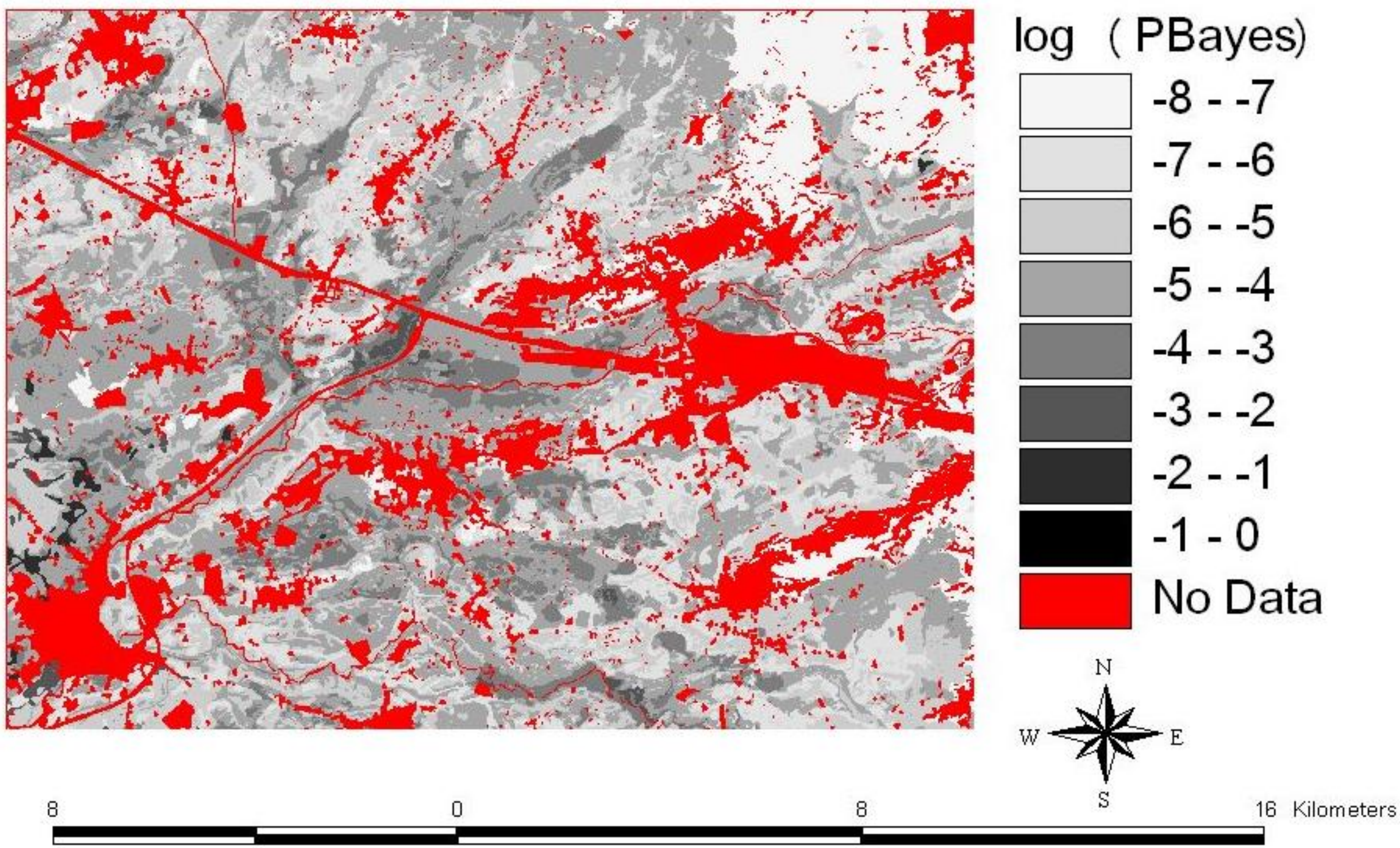
- IRK performance depends on data configuration
  - Random validation fields: poor performance
  - Random validation pixels: excellent performance

Method	Specs	AUC
Predictive Bayes	+ and -	0.81
Predictive Bayes	+	0.60
Inductive Bayes	+ and -	0.81
Inductive Bayes	+	0.47
IRK	Random pixels validation	0.99
IRK	Random fields validation	0.47
Mixed Bayes	**+ and -**	**0.93**
Mixed Bayes	+	0.83



Best map

Probability map for mixed model



Conclusions

1. Bayesian predictive mapping may outperform IRK (depending on data configuration).
2. Bayesian models:
   - Imported deductive models and inductive models based on fuzzy *k*-means clustering performed comparably (AUC);
   - Inductive model passed evidence filter easily, deductive model didn't;
   - Mixed model performed best: Interaction archaeologist/pedometrician!
3. Usage of both + and – data improves performance (AUC+evidence filter).
4. MBF-based evidence filter useful for politically sensitive maps.