ES & Machine Learning

bc³
BASQUE CENTRE
FOR CLIMATE CHANGE
Klima Aldaketa Ikergai

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Machine learning for ecosystem services

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Biodiversity in Sicily

```
/*ML model */
model value of ecology:Biodiversity, uncertainty of value of ecology:Biodiversity
    observing

        @archetype ecology:Vegetation earth:Site with im:High value of ecology:Biodiversity,
        @archetype ecology:Vegetation earth:Site with im:Low  value of ecology:Biodiversity,

        @predictor ecology:NormalizedDifferenceVegetationIndex,
        @predictor ecology:NormalizedDifferenceWaterIndex,
        @predictor distance from landcover:UrbanFabric earth:Region in m,
        @predictor distance from earth:Coast in m,
        @predictor distance from infrastructure:Highway in m,
        @predictor percentage of soil:Silt in soil:TopSoil im:Volume,
        @predictor im:Annual earth:AtmosphericTemperature in Celsius,
        @predictor im:Annual earth:PrecipitationVolume in mm,
        @predictor geography:Aspect in degree_angle,
        @predictor geography:Slope in degree_angle

    using im.weka.bayesnet();
```

Methods: help can come from AI

Category	Task	Common algorithms
Unsupervised learning (learning without feedback from a trainer)	Clustering	k-means
	Associations	Apriori
	Dimensionality reduction	PCA
Supervised learning (learning past actions/decisions with trainer)	Classification (learning a categorical variable)	Bayesian Networks, Decision Trees, Neural Networks
	Regression (learning a continuous variable)	Linear Regression, Perceptron

Environmental Research Letters

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Human dependence on natural resources in rapidly urbanising South African regions

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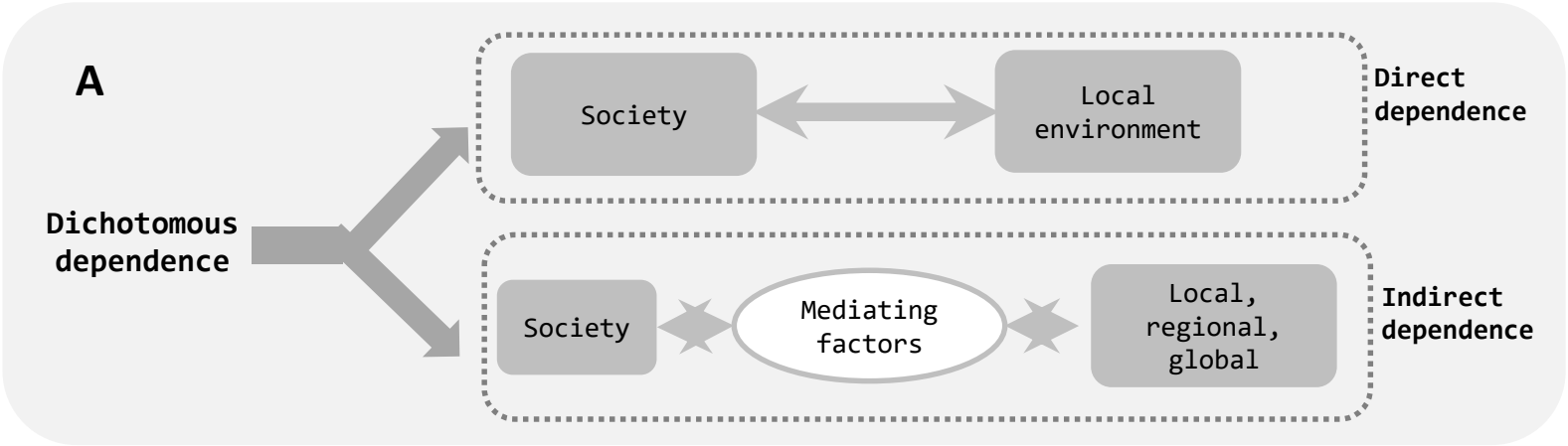
Figures

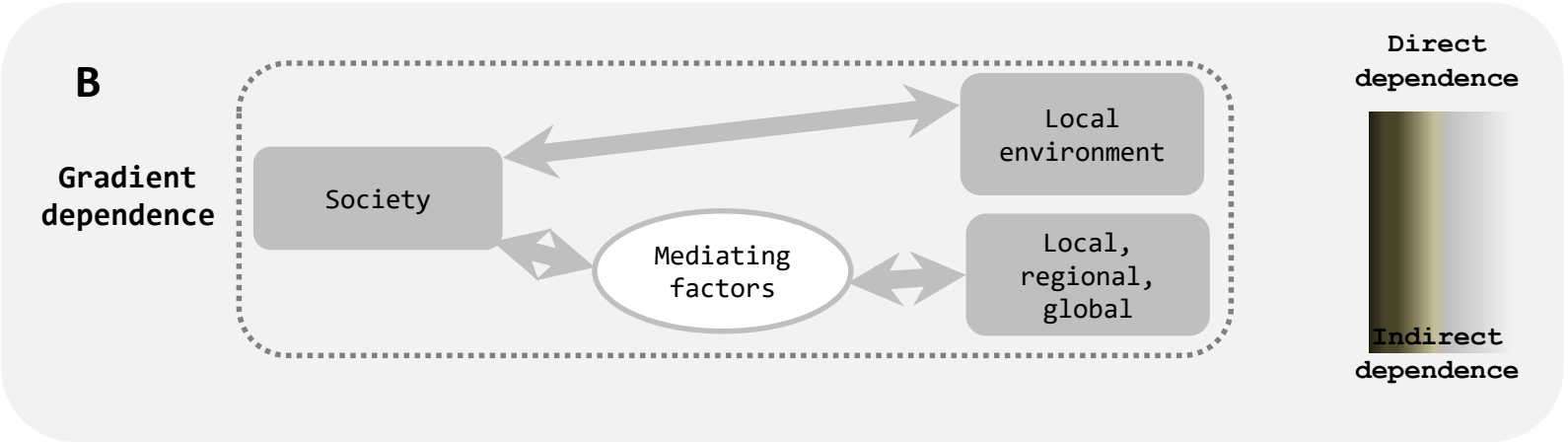
References

What we say in the paper

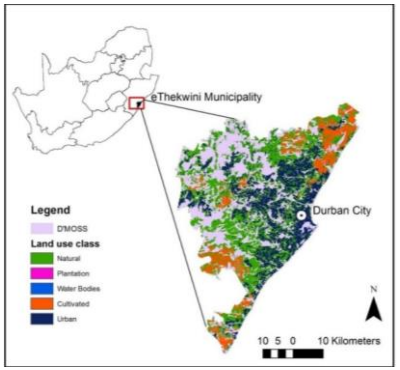
- Dependence on ecosystem services is not dichotomous but a gradient
- Surveys done by national statistics offices are a good source of data to estimate dependence on ES
- Sociodemographic data can equally estimate use of ES (higher frequency and finer resolution)

Dependence is not dichotomous

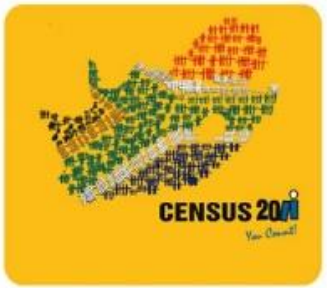


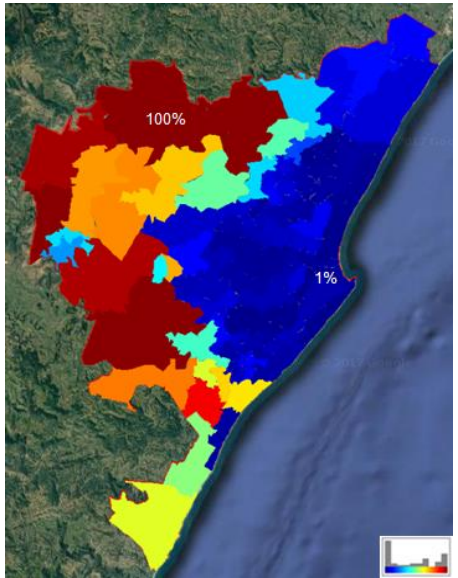


Metric of dependence on ES



Provisioning ES	Natural Resource	Key (Eq.1)
Freshwater use	Water from rivers and springs	pW
Crop production	Crop production in communal areas	pCR
Solid fuels for heating	Firewood and charcoal	pH
Solid fuels for cooking	Firewood and charcoal	pCF
Natural materials for constructing houses	Wood, grass, soil	pB

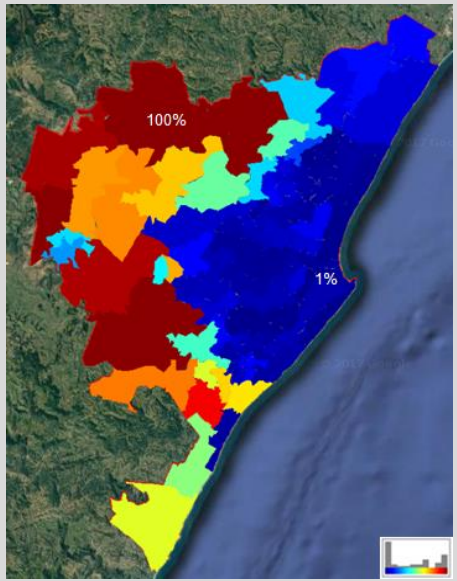




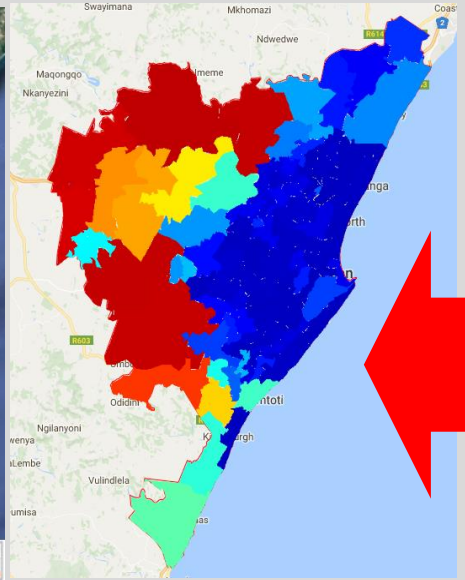
$$ES\ Dep. = 100 * (1 - ((1 - pW) \cdot (1 - pCR) \cdot (1 - pH) \cdot (1 - pCF) \cdot (1 - pB))$$

Sociodemographic data can estimate dependence on ES

Based on reported use

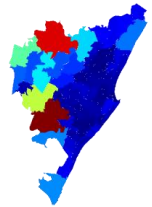


Based on soc-dem data



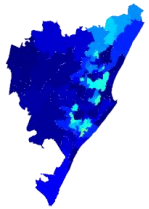
Machine learning cross validation results on training set

Correctly Classified Instances	94	91.2621 %
Incorrectly Classified Instances	9	8.7379 %
Kappa statistic	0.8202	
Mean absolute error	0.0334	
Root mean squared error	0.1132	
Relative absolute error	30.049 %	
Root relative squared error	49.3575 %	
Total Number of Instances	103	

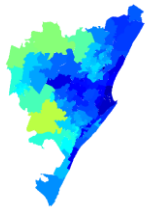


DensityHH

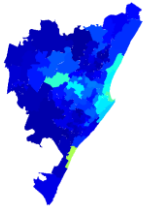
80%



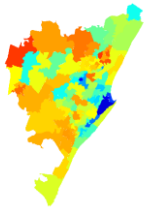
InformalHH



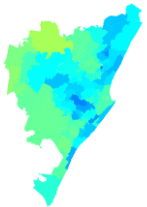
LargeHH



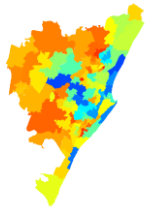
In-migrate



House owned

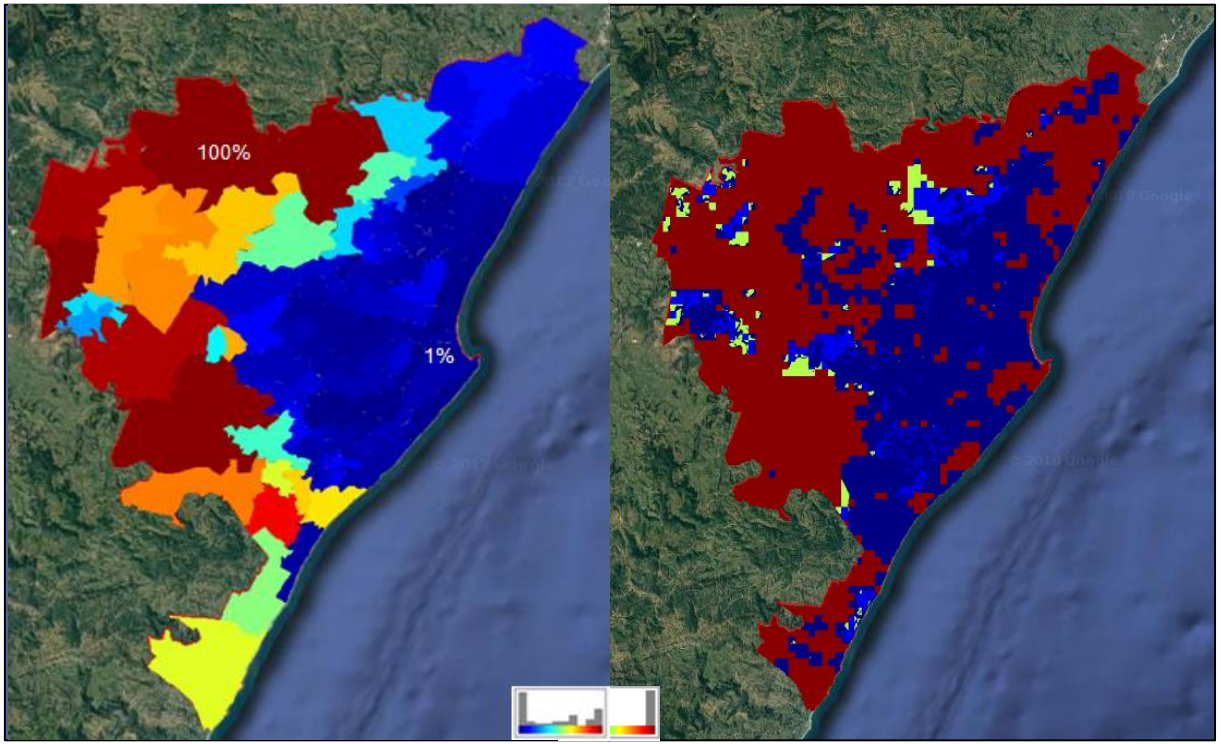


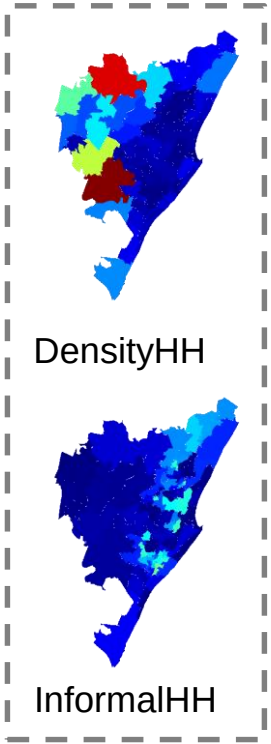
FemaleHead



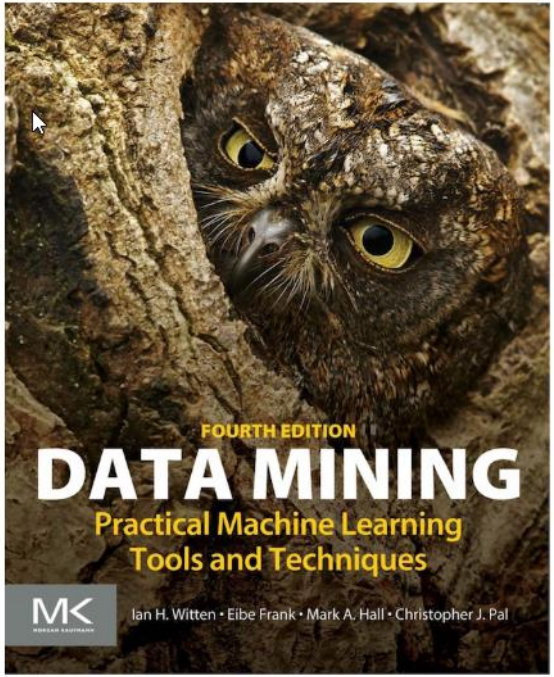
Poverty

Open access socio-dem data: High freq. & finer scale





Weka



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"If you have data that you want to analyze and understand, this book and the associated Weka toolkit are an excellent way to start."

-Jim Gray, Microsoft Research

"The authors provide enough theory to enable practical application, and it is this practical focus that separates this book from most, if not all, other books on this subject."

-Dorian Pyle, Director of Modeling at Numetrics

"This book would be a strong contender for a technical data mining course. It is one of the best of its kind."

-Herb Edelstein, Principal, Data Mining Consultant, Two Crows Consulting

"It is certainly one of my favourite data mining books in my library."

-Tom Breur, Principal, XLNT Consulting, Tiburg, Netherlands

Workflow

Model → Resource → Model