



# ARTIFICIAL INTELLIGENCE AND ENVIRONMENT

# ENVIRONMENTAL PRESSURES

**ENVIRONMENTAL POLLUTION:** Contamination of the physical and biological components of the Earth (air, land, water); Normal environmental processes are adversely affected.

- Pesticides, plastic, ...
- But also light, noise

**CLIMATE CHANGE:** Pollution with greenhouse gasses causes climate change, which in turn affects all forms of life, incl. humans; Changes in temp, precipitation patterns, habitats

**BIODIVERSITY LOSS:** Loss of ecosystem services

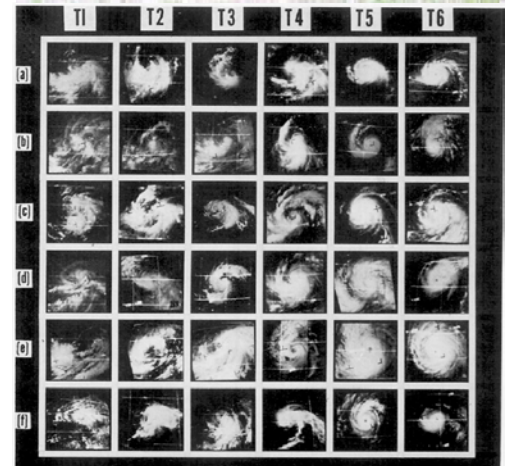


# ADDRESSING ENVIRONMENTAL CHALLENGES w AI

- ENVIRONMENTAL MONITORING
  - Assessing the state of the environment and following it over time
- ENVIRONMENTAL RISK ASSESMENT
  - Assessing the probability of different hazardous and harmful events (fires)
- ENVIRONMENTAL MANAGEMENT
  - Selecting and performing actions to protect the environment

## FUELED BY A FLOOD OF DATA

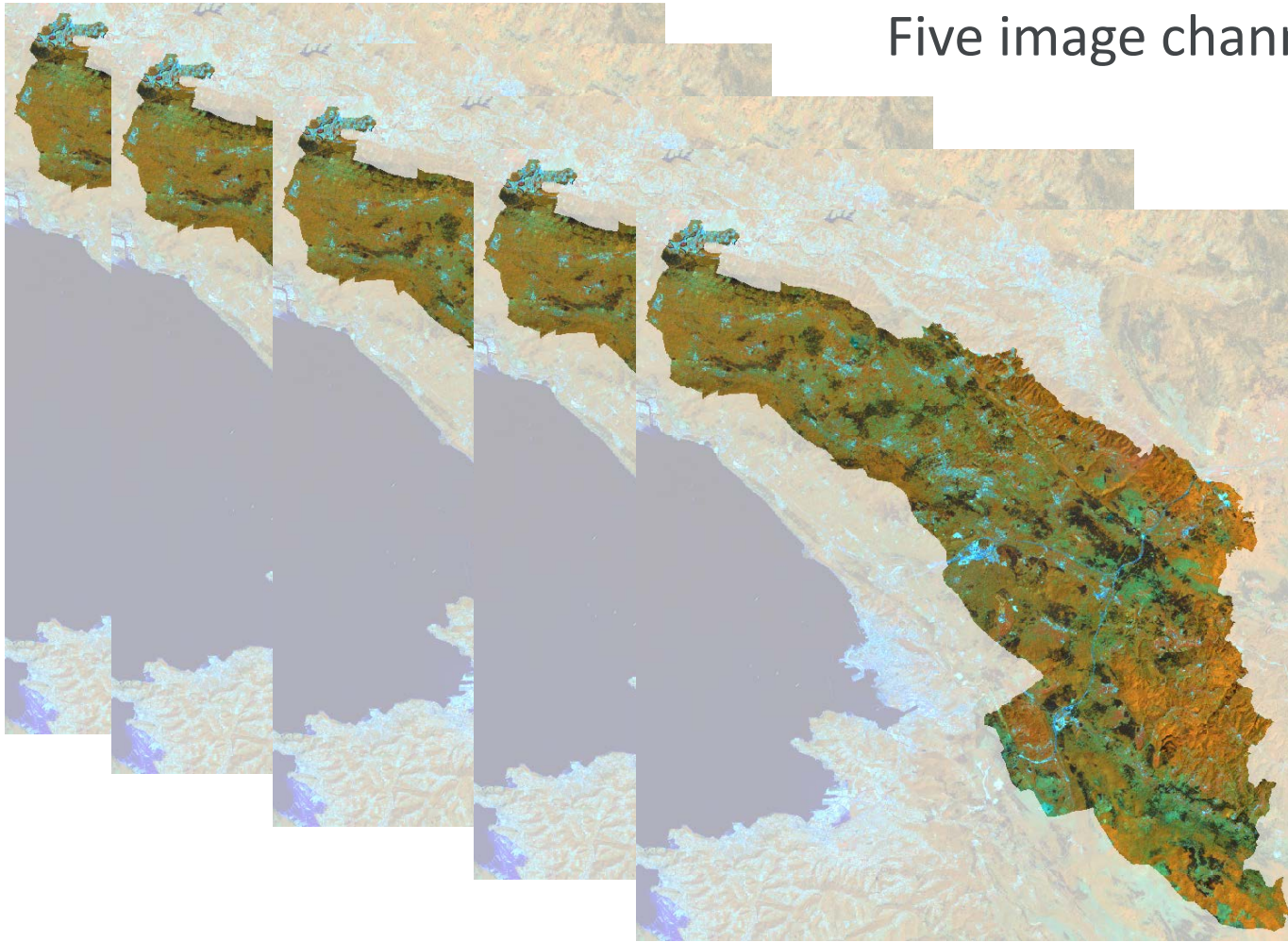
- Earth observation (satellite imagery)
- Drones
- Ground sensors



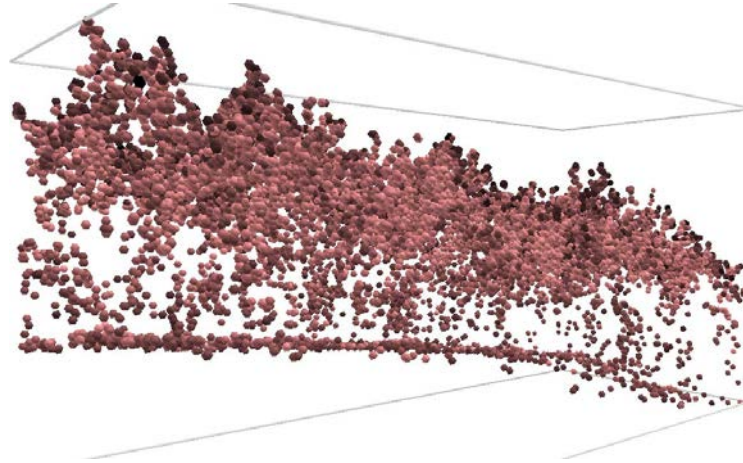
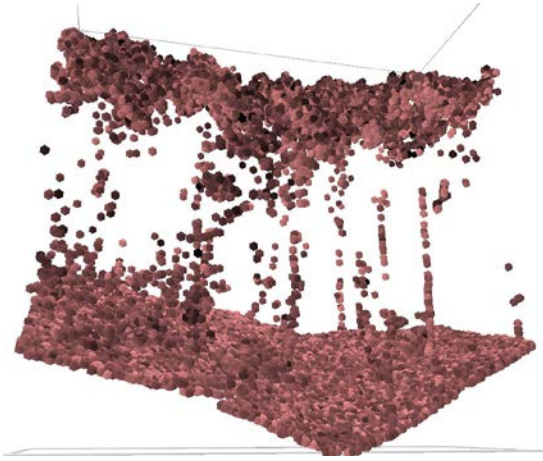
# ESTIMATING THE STATE OF FORESTS IN SLOVENIA FROM REMOTELY SENSED DATA (satellite images)

INPUT: SATELLITE IMAGES (LandSat, MultiSpectral, MultiTemporal)

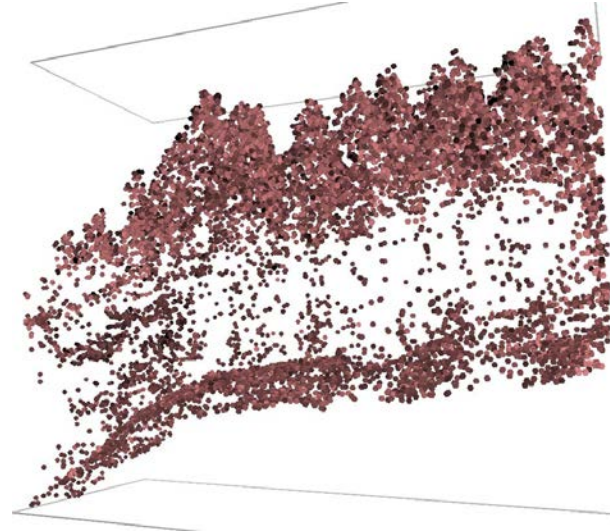
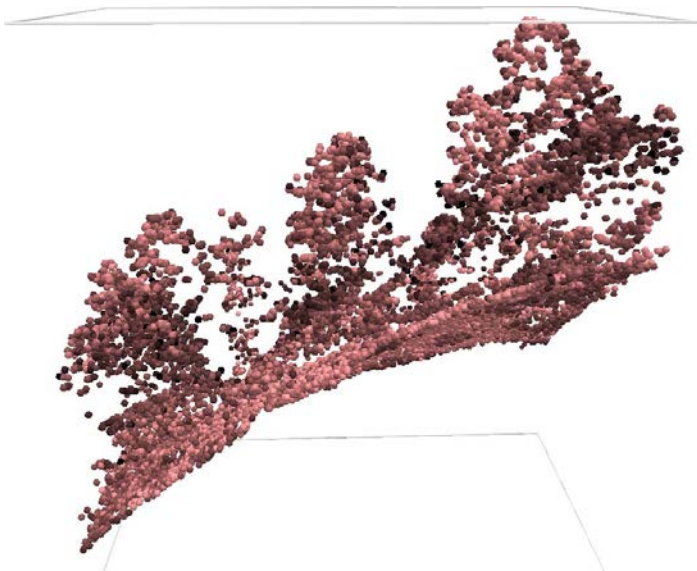
Five image channels: 2,3,4,5,7



# ESTIMATING THE STATE OF FORESTS IN SLOVENIA FROM REMOTELY SENSED DATA (satellite images)



INPUT: LIDAR DATA



# ESTIMATING THE STATE OF FORESTS IN SLOVENIA FROM REMOTELY SENSED DATA (satellite images)

## LIDAR DATA: AREA OF RECORDING



# ESTIMATING THE STATE OF FORESTS IN SLOVENIA FROM REMOTELY SENSED DATA (satellite images)

## THE PREDICTIVE MODELLING TASK:

Predict two very important variables

- Canopy cover/closure: Percentage of bare ground within a square covered by the vertical projection of overlaying vegetation
- Forest stand height: Relative height of vegetation above bare ground

Instead of forest stand height, we can also predict the complete vertical vegetation profile (total 10 vars)

All the target variables derived from LIDAR data

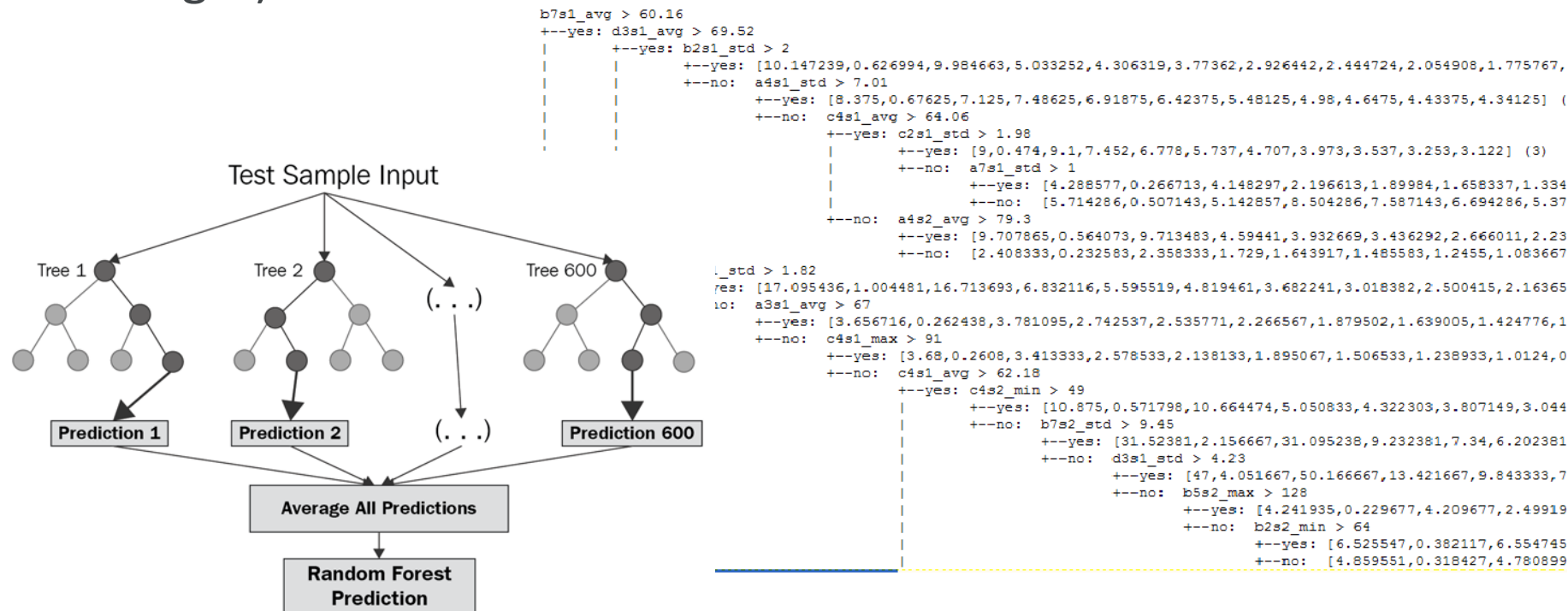
All the attributes/descriptive variables derived from satellite images



# ESTIMATING THE STATE OF FORESTS IN SLOVENIA FROM REMOTELY SENSED DATA (satellite images)

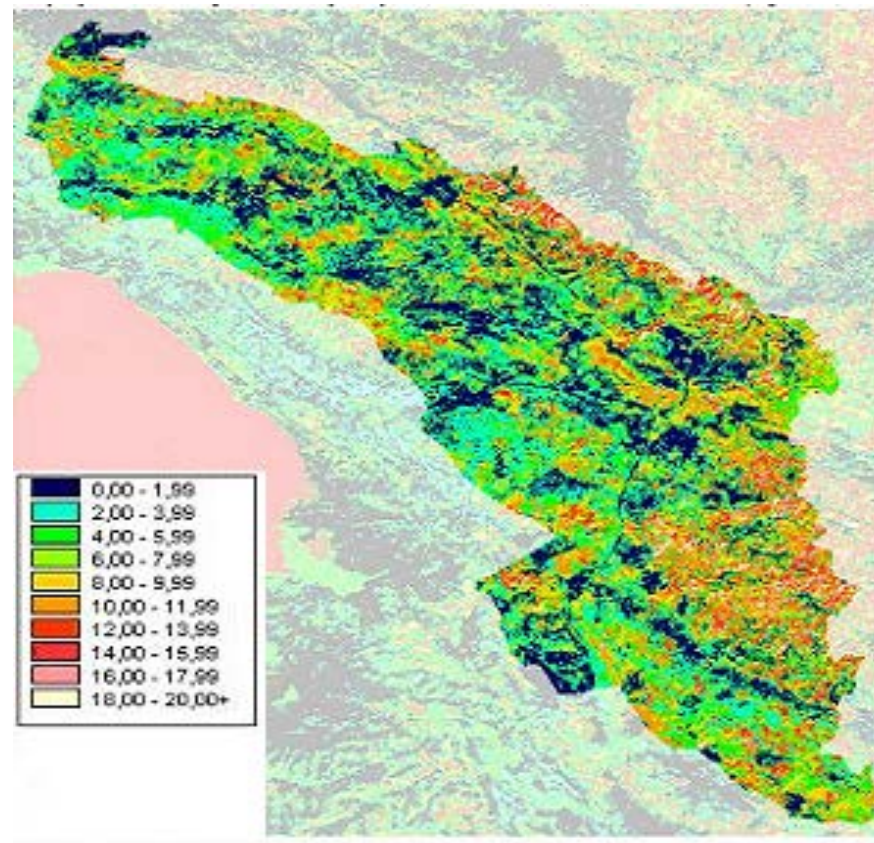
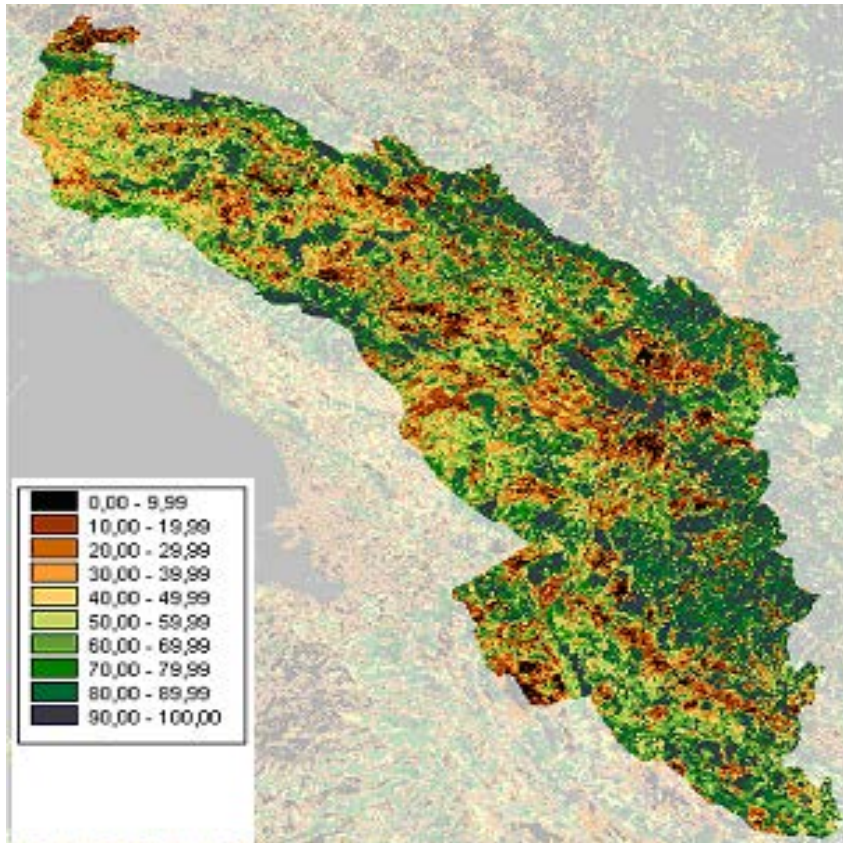
## THE PREDICTIVE MODELLING APPROACH:

Random forests of trees for multi-target regression, simultaneously predicting two (or eleven, if whole vertical profile, not only height) variables



# ESTIMATING THE STATE OF FORESTS IN SLOVENIA FROM REMOTELY SENSED DATA (satellite images)

THE FINAL OUTPUT: Maps of forest height and density, generated by applying the learned models to sat. images of the whole Karst area



# ESTIMATING THE STATE OF FORESTS IN SLOVENIA FROM REMOTELY SENSED DATA (satellite images)

What are the maps good for?

PLANNING FOREST MANAGEMENT

Estimating biomass in the context of carbon emission quotas (forests are a major carbon sink)

ESTIMATING VISIBILITY FOR DIFFERENT LOCATIONS IN THE CONTEXT OF PLANING MOBILE COMMUNICATIONS EQUIPMENT

Estimating the risk of fires



# ESTIMATING THE RISK OF FIRE IN THE NATURAL ENVIRONMENT

Develop models to predict fire outbreaks from

- historical data on fires and
- explanatory data from geographical information systems (GIS)

By using data mining methods

Three models developed for three different regions of Slovenia:

- Kras (Karst) region,
- Primorska (Coastal) region, and
- Continental Slovenia



# ESTIMATING THE RISK OF FIRE IN THE NATURAL ENVIRONMENT

## THE DATA

Data on fire outbreaks for the period 2000-2004 (location, time)

Data on influencing factors

- GIS data
  - Infrastructure
  - Land use
  - Relief
- Multi-temporal MODIS data
- Meteorological ALADIN data
- Fire fuels (forest height/density for the Karst region)

The spatial unit was 1x1 km<sup>2</sup> quadrant



# ESTIMATING THE RISK OF FIRE IN THE NATURAL ENVIRONMENT

## MACHINE LEARNING SETUP

Positive examples: Past fire locations/times

Negative examples randomly sampled (far enough from positive)

Three datasets for different regions of Slovenia

- Kras: 159 attributes and 1439 examples
- Coastal Slovenia: 129 attributes and 2442 examples
- Continental Slovenia: 129 attributes and 8476 examples

Nominal Target attribute that predicts fire outbreak (yes/no)

Several machine learning methods used

- Decision trees
- Classification rules
- Tree ensembles (boosting, bagging, random forests)



# ESTIMATING THE RISK OF FIRE IN THE NATURAL ENVIRONMENT

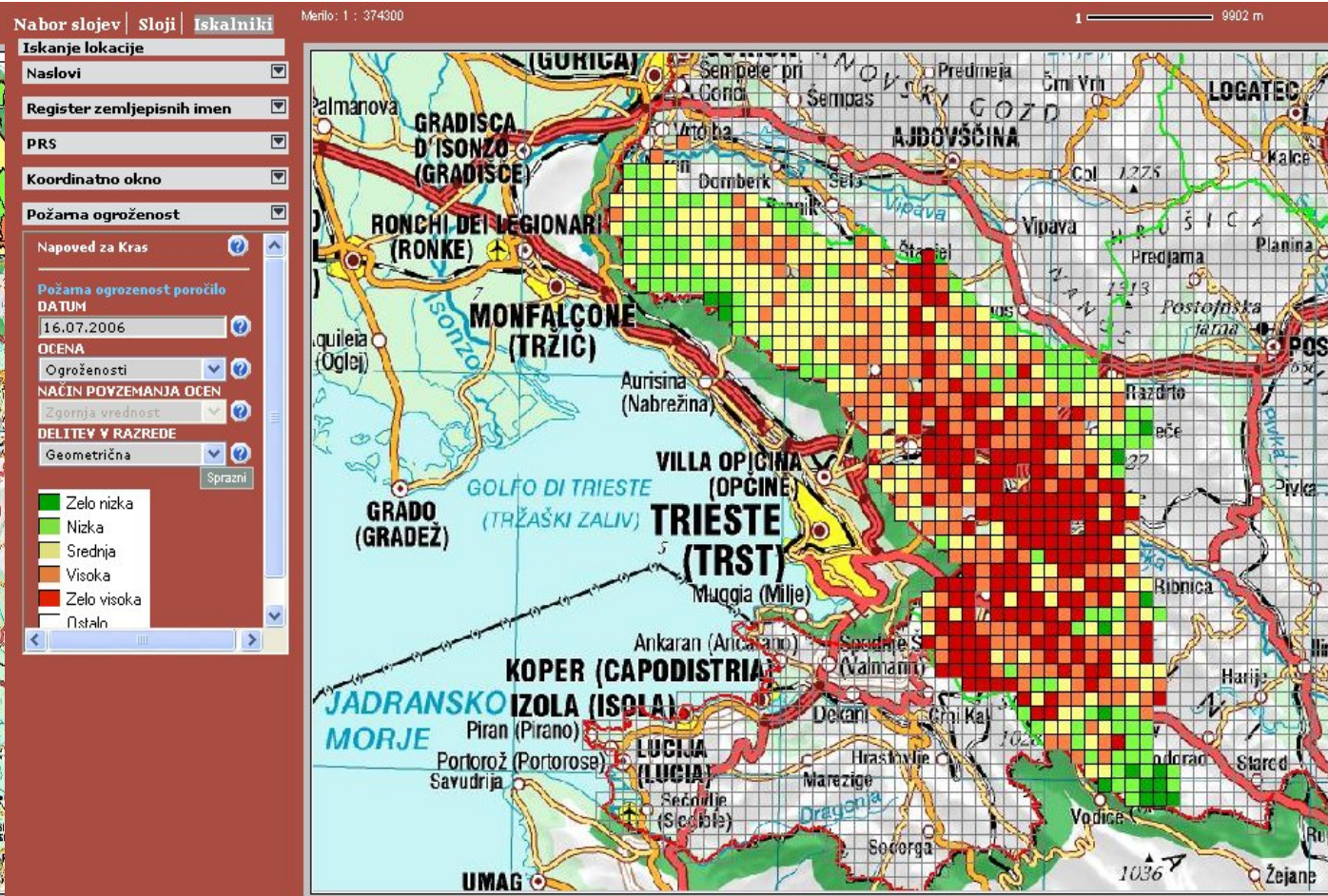
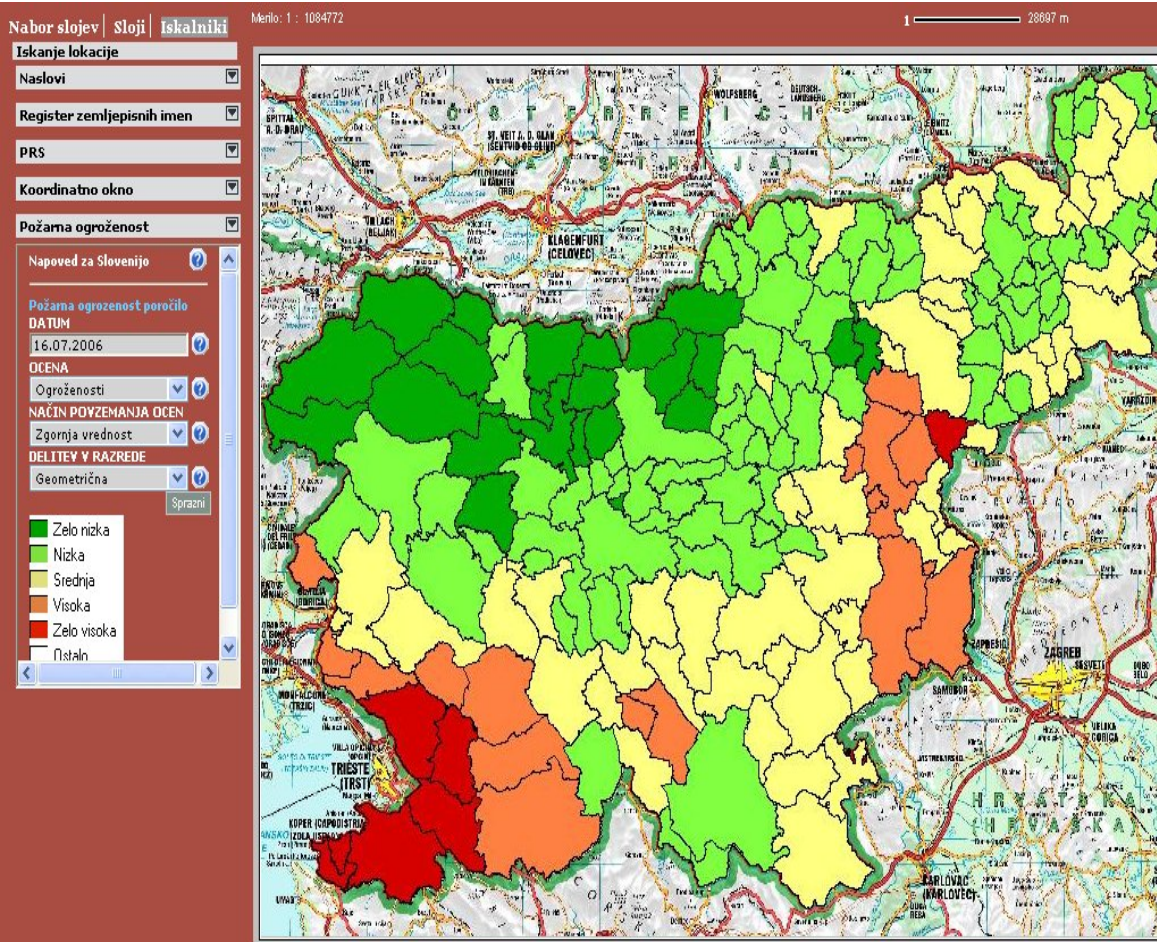
UNDERSTANDABLE RULES for the Karst region show that railways and human activity are important contributors to risk

```
if ((dist_railways ≤ 2970) and (elevation ≥ 378) and (percBuiltUp ≥ 0.875)) then
    fireOutbreak = YES
else if ((percBuiltUp ≥ 0.875) and (dist_railways ≤ 1487) and (percOver ≤ 2.875) and
        (percRiparian ≥ 0.625)) then
    fireOutbreak = YES
else if ((percSwMead ≥ 26) and (percarable ≥ 0.1875) and
        (evapotranspiration_48 ≥ -0.9)) then
    fireOutbreak = YES
else if ((dist_railways ≤ 2970) and (elevation ≥ 350) and (percRiparian ≥ 0.125) and
        (dist_railways ≥ 1897)) then
    fireOutbreak = YES
else
    fireOutbreak = NO
end if
```



# ESTIMATING THE RISK OF FIRE IN THE NATURAL ENVIRONMENT

Risk estimates at municipality level (left) and at 1km x 1km quadrants (right, Karst region)



# ESTIMATING THE RISK OF FIRE IN THE NATURAL ENVIRONMENT

## DEPLOYMENT STATUS

- Included in the GIS (geo. inf. sys.) system e-GIS UJME about natural disasters at the Administration for Civil Protection and Rescue
- Available to and used by the following organizations
  - Firefighter association
  - Administration for civil protection and rescue
  - Environment Agency
  - Forest Service
- Also accessible to the whole range of users of eGIS-UJME (Natural Disasters), incl. municipalities



# RELATING THE ENVIRONMENT AND THE BIOTA: FROM HABITAT MODELS TO COMMUNITY COMPOSITION

# ENVIRONMENT <-> BIOTA

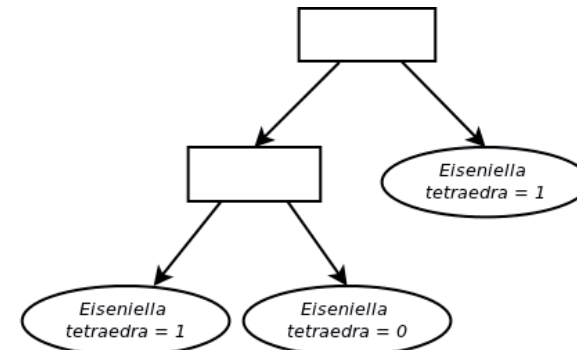
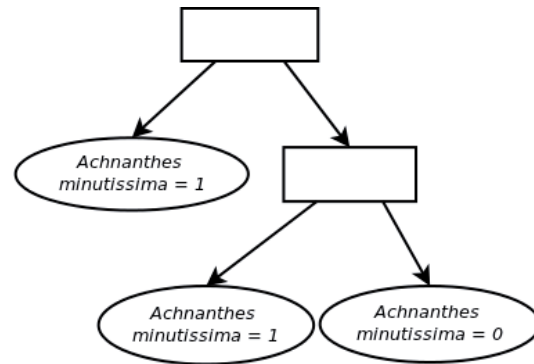
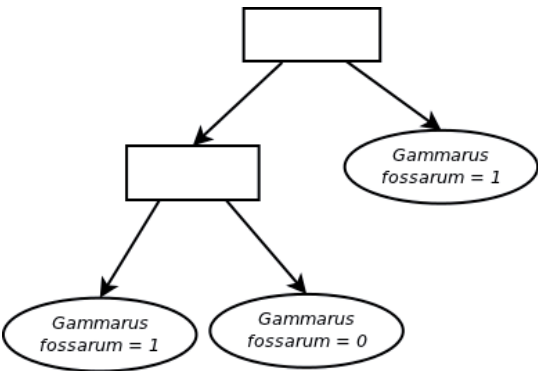
- Predict the biota (or specific components of it)
- At a given site
- From characteristics of the environment at the site
- E.g. predict river water biota from water properties

| Sample ID | Descriptive variables |                                               |                 |      |                 |     | Target variables      |                              |                       |                            |                         |                        |                             |                              |                          |                       |                        |                        |                    |                    |
|-----------|-----------------------|-----------------------------------------------|-----------------|------|-----------------|-----|-----------------------|------------------------------|-----------------------|----------------------------|-------------------------|------------------------|-----------------------------|------------------------------|--------------------------|-----------------------|------------------------|------------------------|--------------------|--------------------|
|           | Temperature           | K <sub>2</sub> Cr <sub>2</sub> O <sub>7</sub> | NO <sub>2</sub> | Cl   | CO <sub>2</sub> | ... | <i>Cladophora</i> sp. | <i>Gongrosira incrustans</i> | <i>Oedogonium</i> sp. | <i>Stigeoclonium tenue</i> | <i>Melosira varians</i> | <i>Nitzschia palea</i> | <i>Audouinella chalybea</i> | <i>Erpobdella octoculata</i> | <i>Gammarus fossarum</i> | <i>Baetis rhodani</i> | <i>Hydropsyche</i> sp. | <i>Rhyacophila</i> sp. | <i>Simulim</i> sp. | <i>Tubifex</i> sp. |
| ID1       | 0.66                  | 0.00                                          | 0.40            | 1.46 | 0.84            | ... | 1                     | 0                            | 0                     | 0                          | 0                       | 1                      | 1                           | 0                            | 1                        | 1                     | 1                      | 1                      | 1                  | 1                  |
| ID2       | 2.03                  | 0.16                                          | 0.35            | 1.74 | 0.71            | ... | 0                     | 1                            | 0                     | 1                          | 1                       | 1                      | 1                           | 0                            | 1                        | 1                     | 1                      | 1                      | 1                  | 0                  |
| ID3       | 3.25                  | 0.70                                          | 0.46            | 0.78 | 0.71            | ... | 1                     | 1                            | 0                     | 0                          | 1                       | 0                      | 1                           | 0                            | 1                        | 1                     | 1                      | 0                      | 1                  | 1                  |
| ...       | ...                   | ...                                           | ...             | ...  | ...             | ... | ...                   | ...                          | ...                   | ...                        | ...                     | ...                    | ...                         | ...                          | ...                      | ...                   | ...                    | ...                    | ...                | ...                |



# HABITAT MODELING

- Model the presence & absence (abundance) of each species separately

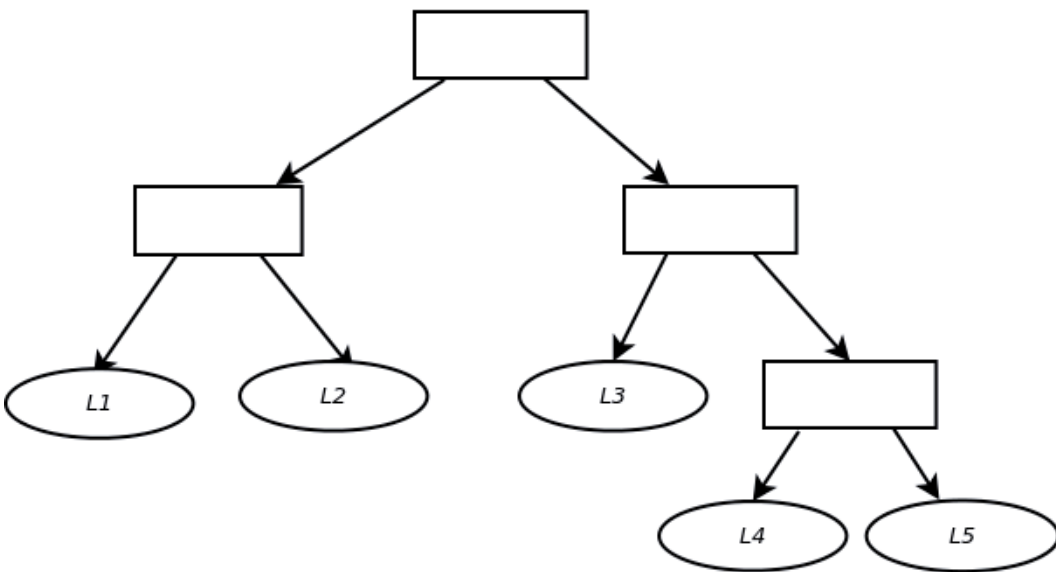


- Binary Classification (Regression)



# PREDICTING SPECIES COMPOSITION

- One model for **all the species at once**



L1:  
Gammarus fossarum: 0  
Achnanthes minutissima: 1  
Eiseniella tetraedra: 1

L2:  
Gammarus fossarum: 0  
Achnanthes minutissima: 1  
Eiseniella tetraedra: 0

L3:  
Gammarus fossarum: 1  
Achnanthes minutissima: 1  
Eiseniella tetraedra: 1

L4:  
Gammarus fossarum: 1  
Achnanthes minutissima: 1  
Eiseniella tetraedra: 0

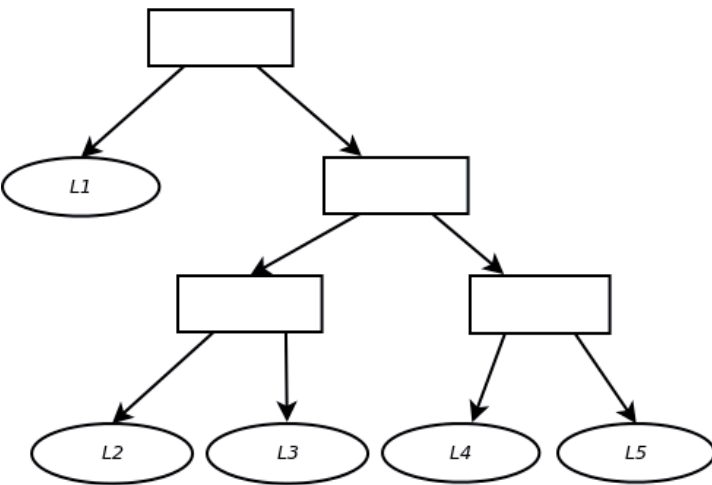
L5:  
Gammarus fossarum: 0  
Achnanthes minutissima: 1  
Eiseniella tetraedra: 1

- Multi-target classification/regression**



# PREDICTING COMMUNITY STRUCTURE

- One model for all of the species at once, additionally using the taxonomical hierarchy



L1:

*Amphipoda* : 1  
*Gammarus* : 1  
*Gammarus fossarum* : 1  
*Gammarus lacustris* : 0

*Bacillariophyta* : 1  
*Achnanthes* : 1  
*Achnanthes minutissima* : 1  
*Eiseniella* : 0  
*Eiseniella tetraedra* : 0

L3:

*Amphipoda* : 1  
*Gammarus* : 1  
*Gammarus fossarum* : 0  
*Gammarus lacustris* : 1

*Bacillariophyta* : 1  
*Achnanthes* : 1  
*Achnanthes minutissima* : 1  
*Eiseniella* : 0  
*Eiseniella tetraedra* : 0

L5:

*Amphipoda* : 1  
*Gammarus* : 1  
*Gammarus fossarum* : 1  
*Gammarus lacustris* : 1

*Bacillariophyta* : 1  
*Achnanthes* : 0  
*Achnanthes minutissima* : 0  
*Eiseniella* : 1  
*Eiseniella tetraedra* : 1

L2:

*Amphipoda* : 1  
*Gammarus* : 1  
*Gammarus fossarum* : 1  
*Gammarus lacustris* : 1

*Bacillariophyta* : 0  
*Achnanthes* : 0  
*Achnanthes minutissima* : 0  
*Eiseniella* : 0  
*Eiseniella tetraedra* : 0

L4:

*Amphipoda* : 1  
*Gammarus* : 1  
*Gammarus fossarum* : 1  
*Gammarus lacustris* : 0

*Bacillariophyta* : 1  
*Achnanthes* : 1  
*Achnanthes minutissima* : 1  
*Eiseniella* : 1  
*Eiseniella tetraedra* : 1

- Hierarchical multi-label classification



# SLOVENIAN RIVERS

1.060 samples

16 physical and chemical props.

of water, 491 species

data collected in 1990-1995



## *ephemeroptera*

*ephemeroptera\_acantrella*

*ephemeroptera\_acantrella\_sinaica*

*ephemeroptera\_baetidae*

*ephemeroptera\_baetis*

*ephemeroptera\_baetis\_alpinus*

*ephemeroptera\_baetis\_buceratus*

*ephemeroptera\_baetis\_fuscatus*

*ephemeroptera\_baetis\_muticus*

***ephemeroptera\_baetis\_rhodani***

*ephemeroptera\_baetis\_scambus*

*ephemeroptera\_baetis\_venus*

*ephemeroptera\_ecdyonurus*

*ephemeroptera\_ecdyonurus\_forcipula*

*ephemeroptera\_ecdyonurus\_helveticus*

*ephemeroptera\_ecdyonurus\_insignis*

*ephemeroptera\_ecdyonurus\_torrentis*

*ephemeroptera\_ecdyonurus\_venosus*

*ephemeroptera\_electrogena*

*ephemeroptera\_electrogena\_lateralis*

*ephemeroptera\_electrogena\_quadrilineata*

## *plecoptera*

*plecoptera\_amphinemura*

*plecoptera\_amphinemura\_triangularis*

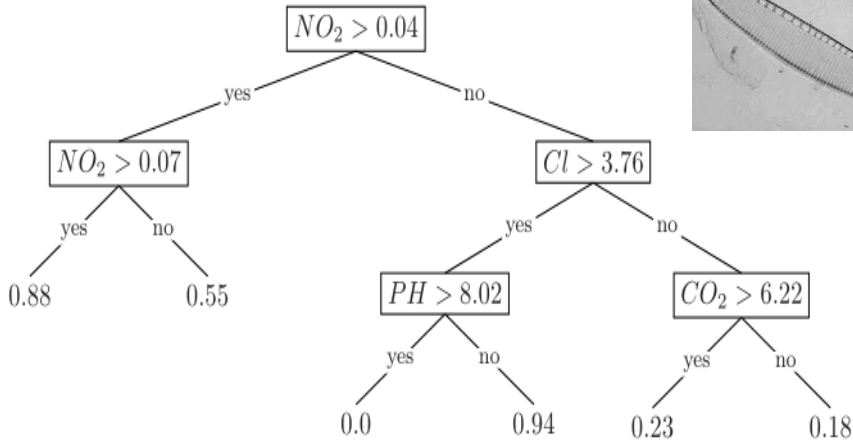
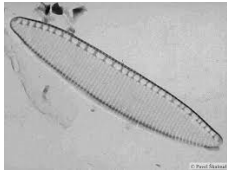
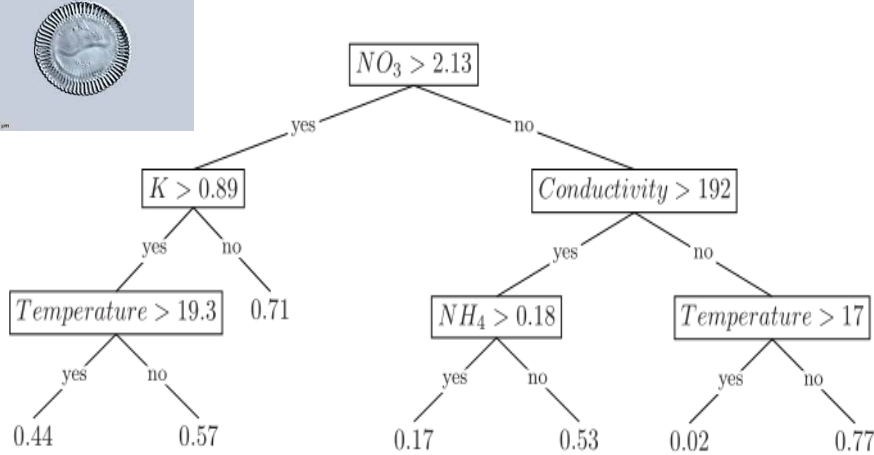
*plecoptera\_brachyptera*

***plecoptera\_brachyptera\_risi***

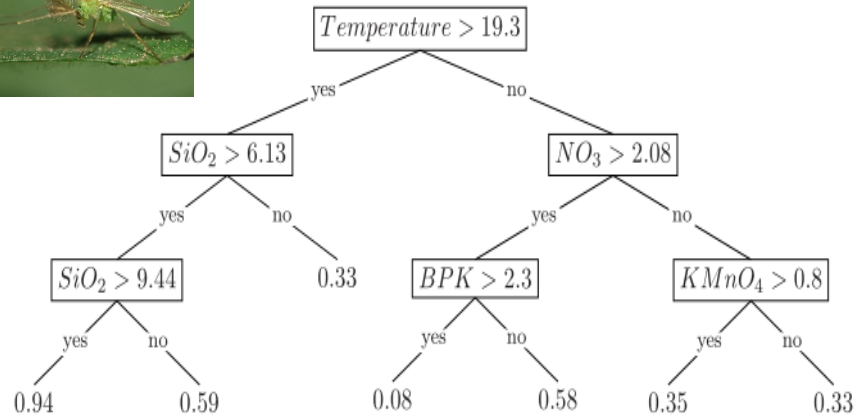
*plecoptera\_brachyptera\_seticornis*



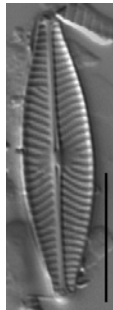
# SLOVENIAN RIVERS: HABITAT MODELS



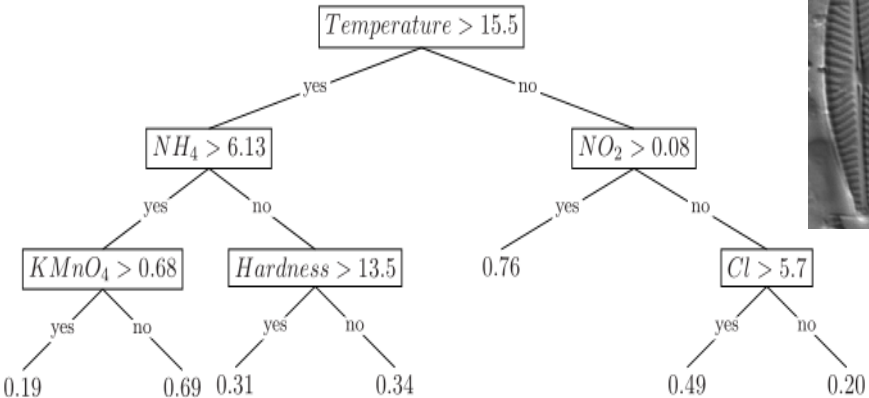
*Bacillariophyta Cyclotella Comta*



*Diptera Chironomidae Zeleni*



*Bacillariophyta Nitzschia Palea*

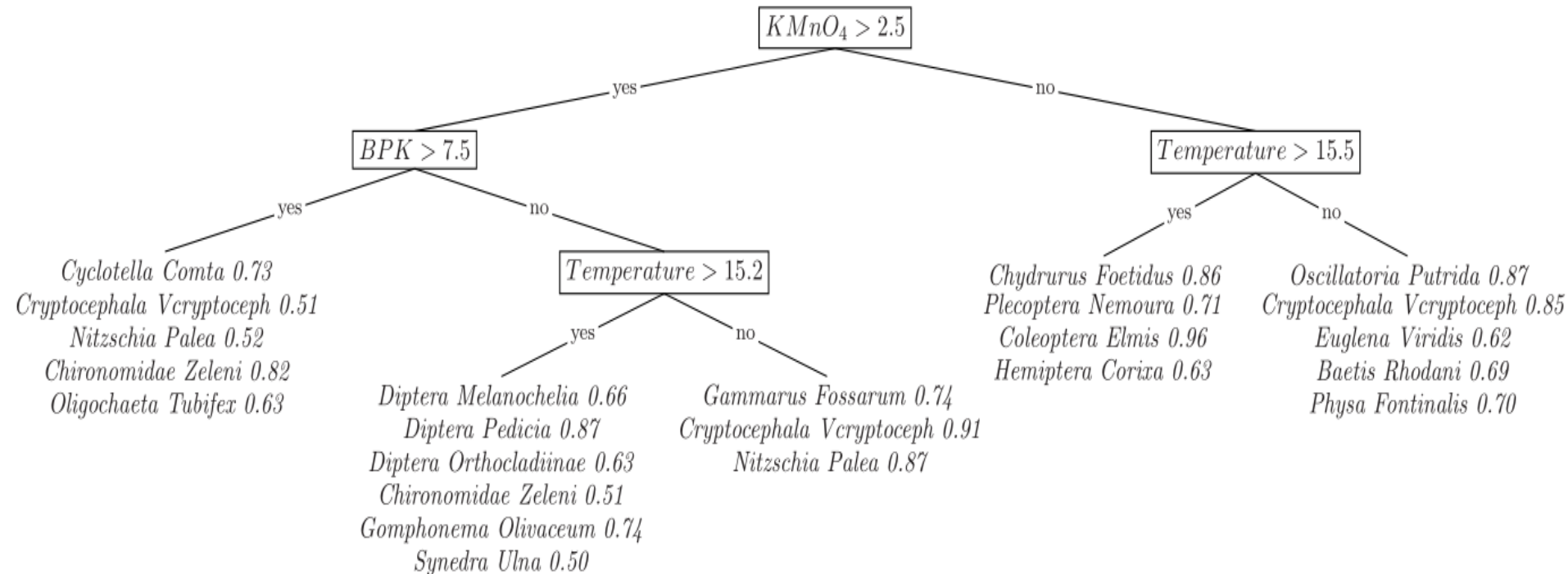


*Bacillariophyta Navicula Cryptocephala Vcryptoceph*

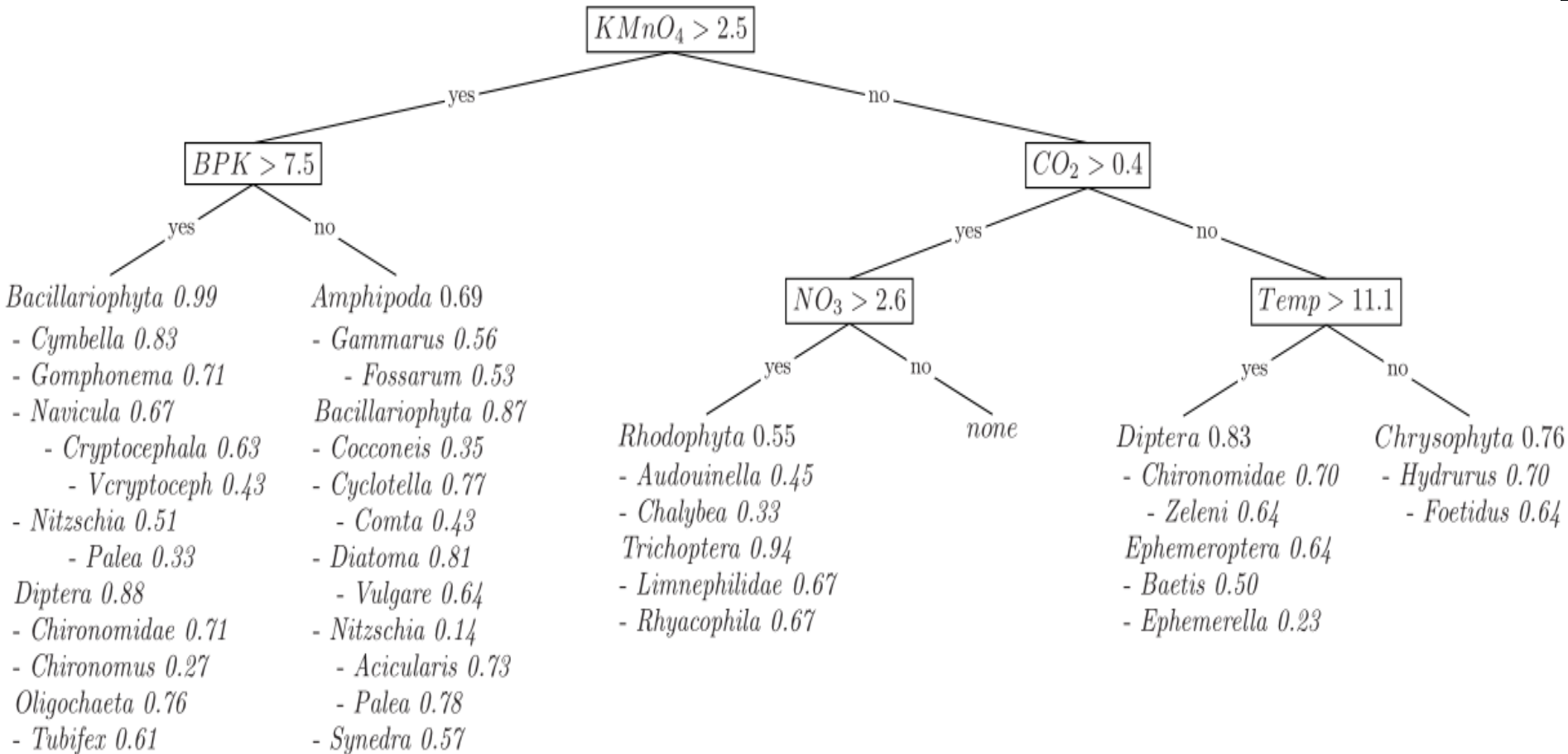


# SLOVENIAN RIVERS: SPECIES COMP.

- MLC: Multi-label classification tree



# SLOVENIAN RIVERS: COMMUNITY STRUC.



# DANISH FARMS: SOIL MICROARTHROPODS

- 1.944 soil samples
- 137 attributes/agricultural events and soil biological parameters
- 35 collembolan species
- data collected 1989-1993



## *Isotominae*

### *Isotominae\_Isotoma*

*Isotominae\_Isotoma\_anglicana*

*Isotominae\_Isotoma\_notabilis*

*Isotominae\_Isotoma\_tigrina*

## *Lepidocyrtinae*

### *Lepidocyrtinae\_Lepidocyrtus*

*Lepidocyrtinae\_Lepidocyrtus\_cyaneus*

*Lepidocyrtinae\_Lepidocyrtus\_lanuginosus*

### *Lepidocyrtinae\_Pseudosinella*

*Lepidocyrtinae\_Pseudosinella\_alba*

*Lepidocyrtinae\_Pseudosinella\_sexoculata*

## *Orchesellinae*

### *Orchesellinae\_Heteromurus*

*Orchesellinae\_Heteromurus\_nitidus*

### *Orchesellinae\_Orchesella*

*Orchesellinae\_Orchesella\_cincta*

*Orchesellinae\_Orchesella\_villosa*

## *Sminthuridae*

### *Sminthuridae\_Smint*

### *Sminthuridae\_Sminthurinus*

*Sminthuridae\_Sminthurinus\_aureus*

*Sminthuridae\_Sminthurinus\_elegans*

### *Sminthuridae\_Sminthurus*

*Sminthuridae\_Sminthurus\_viridis*

## *Tomoceridae*

### *Tomoceridae\_Tomocerus*

*Tomoceridae\_Tomocerus\_flavescens*

*Tomoceridae\_Tomocerus\_minor*

## *Tullbergiidae*

*Tullbergiidae\_Mesaphorura*



# VICTORIA, AUSTRALIA

## VEGETATION

27.482 sites

81 env. attributes

3.173 species



### *DivisionConifer*

#### *DivisionConifer\_callitris*

*DivisionConifer\_callitris\_endlicheri*

*DivisionConifer\_callitris\_glaucophylla*

*DivisionConifer\_callitris\_gracilis*

*DivisionConifer\_callitris\_gracilis\_ssp~murrayensis*

*DivisionConifer\_callitris\_rhomboidea*

*DivisionConifer\_callitris\_verrucosa*

### *DivisionMonocotyledon*

#### *DivisionMonocotyledon\_leucopogon*

*DivisionMonocotyledon\_leucopogon\_attenuatus*

*DivisionMonocotyledon\_leucopogon\_australis*

*DivisionMonocotyledon\_leucopogon\_clelandii*

*DivisionMonocotyledon\_leucopogon\_juniperinus*

*DivisionMonocotyledon\_leucopogon\_lanceolatus*

*DivisionMonocotyledon\_leucopogon\_lanceolatus\_var~lanceolatus*

*DivisionMonocotyledon\_leucopogon\_maccraei*

***DivisionMonocotyledon\_leucopogon\_microphyllus***

*DivisionMonocotyledon\_leucopogon\_microphyllus\_var~pilibundus*

*DivisionMonocotyledon\_leucopogon\_montanus*

*DivisionMonocotyledon\_leucopogon\_neurophyllus*

*DivisionMonocotyledon\_leucopogon\_parviflorus*

*DivisionMonocotyledon\_leucopogon\_virgatus*

*DivisionMonocotyledon\_leucopogon\_virgatus\_var~brevifolius*

*DivisionMonocotyledon\_leucopogon\_virgatus\_var~virgatus*

*DivisionMonocotyledon\_leucopogon\_woodsii*

#### *DivisionMonocotyledon\_epacris*

*DivisionMonocotyledon\_epacris\_breviflora*

*DivisionMonocotyledon\_epacris\_celata*

*DivisionMonocotyledon\_epacris\_glacialis*

*DivisionMonocotyledon\_epacris\_gunnii*

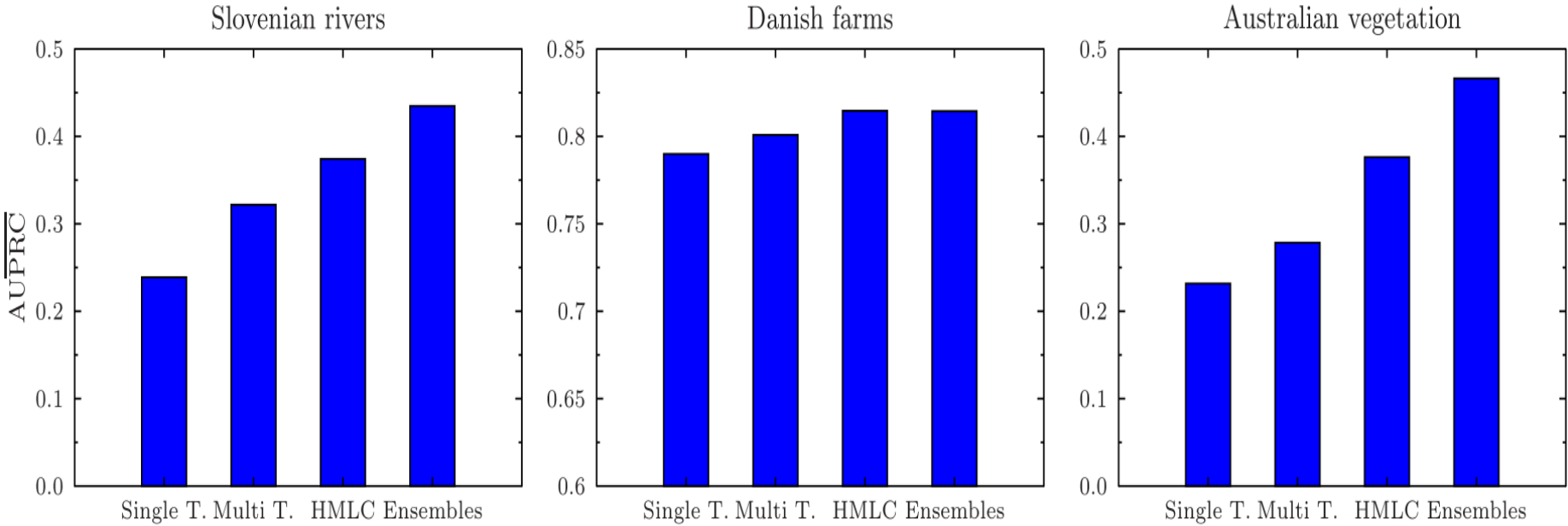
***DivisionMonocotyledon\_epacris\_impressa***

*DivisionMonocotyledon\_epacris\_impressa\_var~grandiflora*

*DivisionMonocotyledon\_epacris\_impressa\_var~impressa*



# COMMUNITY STRUCTURE: OVERALL RESULTS



| Dataset               | Method       | AUPRC        | $O_5$ | Learning time | Complexity |
|-----------------------|--------------|--------------|-------|---------------|------------|
| Slovenian rivers      | Single-label | 0.239        | 0.692 | 23.3          | 15,336     |
|                       | HSC          | 0.309        | 0.591 | 10.2          | 25,035     |
|                       | Multi-label  | 0.322        | 0.007 | 9.4           | 1          |
|                       | HMC          | <b>0.374</b> | 0.132 | 0.6           | 37         |
| Danish farms          | Single-label | 0.790        | 0.099 | 3.7           | 2605       |
|                       | HSC          | 0.808        | 0.083 | 1.3           | 2873       |
|                       | Multi-label  | 0.801        | 0.112 | 0.7           | 265        |
|                       | HMC          | <b>0.815</b> | 0.065 | 0.4           | 259        |
| Australian vegetation | Single-label | 0.232        | 0.715 | 14,888.2      | 482,745    |
|                       | HSC          | 0.306        | 0.591 | 76,023.2      | 648,970    |
|                       | Multi-label  | 0.278        | 0.684 | 4639.5        | 23,699     |
|                       | HMC          | <b>0.376</b> | 0.180 | 313.5         | 1279       |





# EXAMPLES OF USING PROCESS-BASED MODELLING

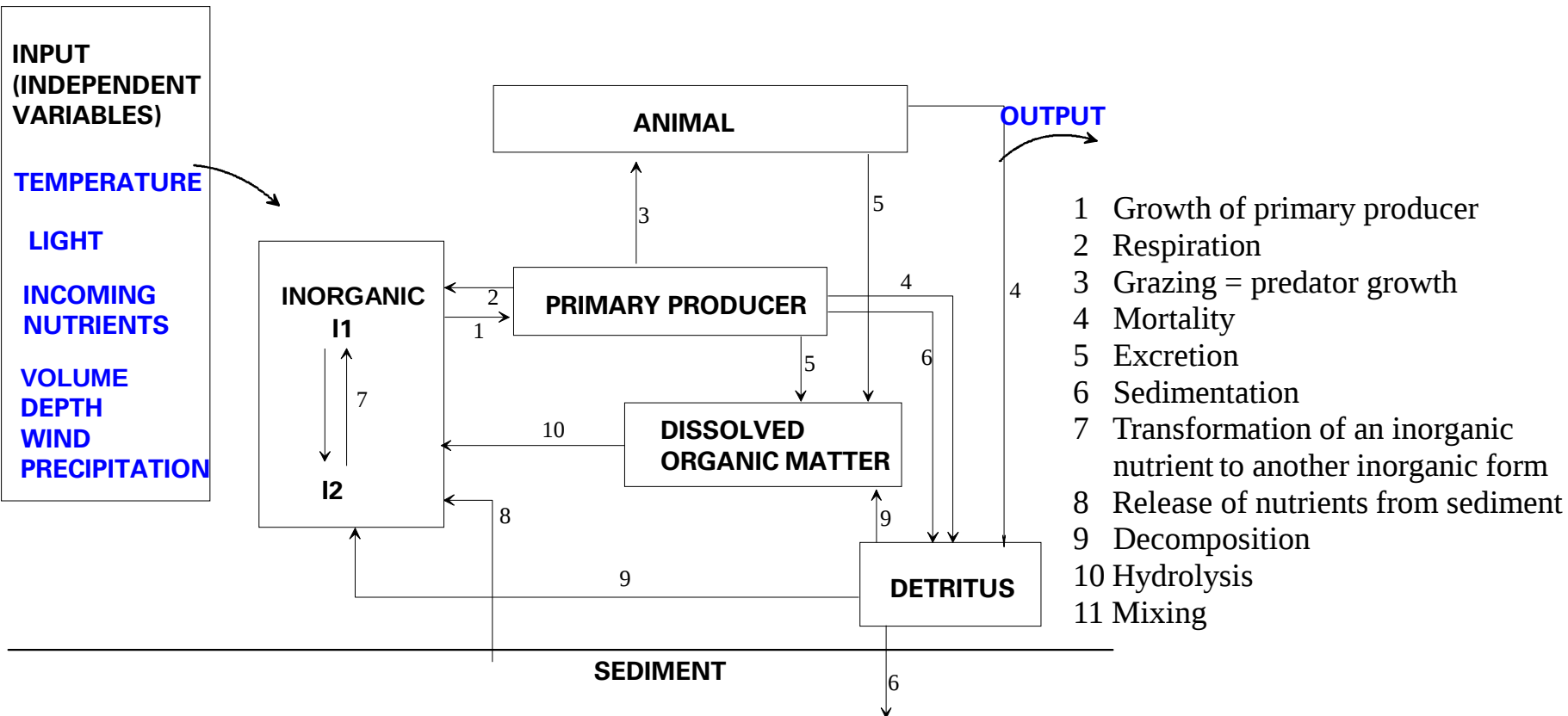
# SYSTEMS ECOLOGY

- Population ecology, esp. population dynamics
- Mostly for aquatic ecosystems
- Library of domain knowledge about modeling population dynamics in aquatic ecosystems: PhD thesis of Natasa Atanasova
- Used for modeling many different aquatic ecosystems
  - Lagoon of Venice
  - Ross Sea, Antarctica
  - Lakes (Bled - Slovenia, Glumsoe - Denmark, Greifensee, Zuerich – Switzerland, Kasumigaura - Japan, Kinneret - Israel)



# KNOWLEDGE FOR MODELING AQUATIC ECOSYSTEMS

An overview of entities and processes in the library



# AQUATIC ECOSYSTEMS MODELLED

- Same library of domain knowledge re-used to model
  - Venice Lagoon

$$\begin{aligned} \dot{\text{biomass}} = & 4.79 \cdot 10^{-5} \cdot \text{biomass} \cdot \left(1 - \frac{\text{biomass}}{0.844}\right) \\ & + 0.406 \cdot \text{biomass} \cdot (1 - e^{-0.216 \cdot \text{temp}}) \cdot (1 - e^{-0.413 \cdot \text{DO}}) \cdot \frac{\text{NH}_3}{\text{NH}_3 + 1} \\ & - 0.0343 \cdot \text{biomass} \end{aligned}$$

- Ross Sea, Antarctica
- Many lake ecosystems
  - Lake Kinneret: Israel
  - Lakes Zurich, Greifensee: Switzerland
  - Lake Kasumigaura: Japan
  - Lake Bled, Slovenia:
  - Lake Glumsoe: Denmark



# AUTOMATED MODELING OF LAKE ECOSYSTEMS

|                                                                                                               | Depth.<br>Avg. | Volume<br>m <sup>3</sup> | Time of<br>measurement                  | Data used<br>for modeling                                 | Sampling<br>frequency        |
|---------------------------------------------------------------------------------------------------------------|----------------|--------------------------|-----------------------------------------|-----------------------------------------------------------|------------------------------|
| <b>Lake Glumsoe</b><br>       | 2              | 532 000                  | Apr.73-Apr.74<br>and<br>Oct.74 - Oct.75 | temp, light,<br>nutrients,<br>Chl-a,<br>zoo               | daily                        |
| <b>Lake Bled</b><br>          | 18             | 25<br>MIO                | 1995 to 2002                            | load, temp,<br>light<br>nutrients,<br>total_phyto<br>zoo. | monthly                      |
| <b>Lake Greifensee</b><br>   | 18             | 148<br>MIO               | 1988 to 1999                            | load,<br>nutrients,<br>Chl-a,<br>zoo                      | two weeks<br>to one<br>month |
| <b>Lake Kasumigaura</b><br> | 4              | 880<br>MIO               | 1986 – 1992                             | load,<br>nutrients,<br>Chl-a,<br>zoo                      | monthly                      |



# LAKE GLUMSOE: THE DATA

- For several years, the lake had been receiving mechanically-biologically treated waste water from a community with 3,000 inhabitants.
- The lake's contributing area (10.9 km<sup>2</sup>) is mainly agricultural, which represents an additional source of nitrogen and phosphorus.
- The high nitrogen and phosphorus concentration in the treated waste water has caused hypereutrophication.



# LAKE GLUMSOE: THE DATA

- The data set includes two years of daily measurements from April, 1973 to April, 1974 and from October 1974 to October, 1975.
  - through flow
  - dissolved inorganic nitrogen (ns) [mg/l]
  - dissolved inorganic phosphorus (ps) v [mg/l]
  - phytoplankton concentration (phyto) in [mg Chl-a/l]
  - zooplankton concentration (zoo) in [mg DW/l]
  - temperature (temp)
  - sunlight intensity [J/(cm<sup>2</sup>\*day)]
- The task: to discover a phytoplankton growth model with Automated Modeling

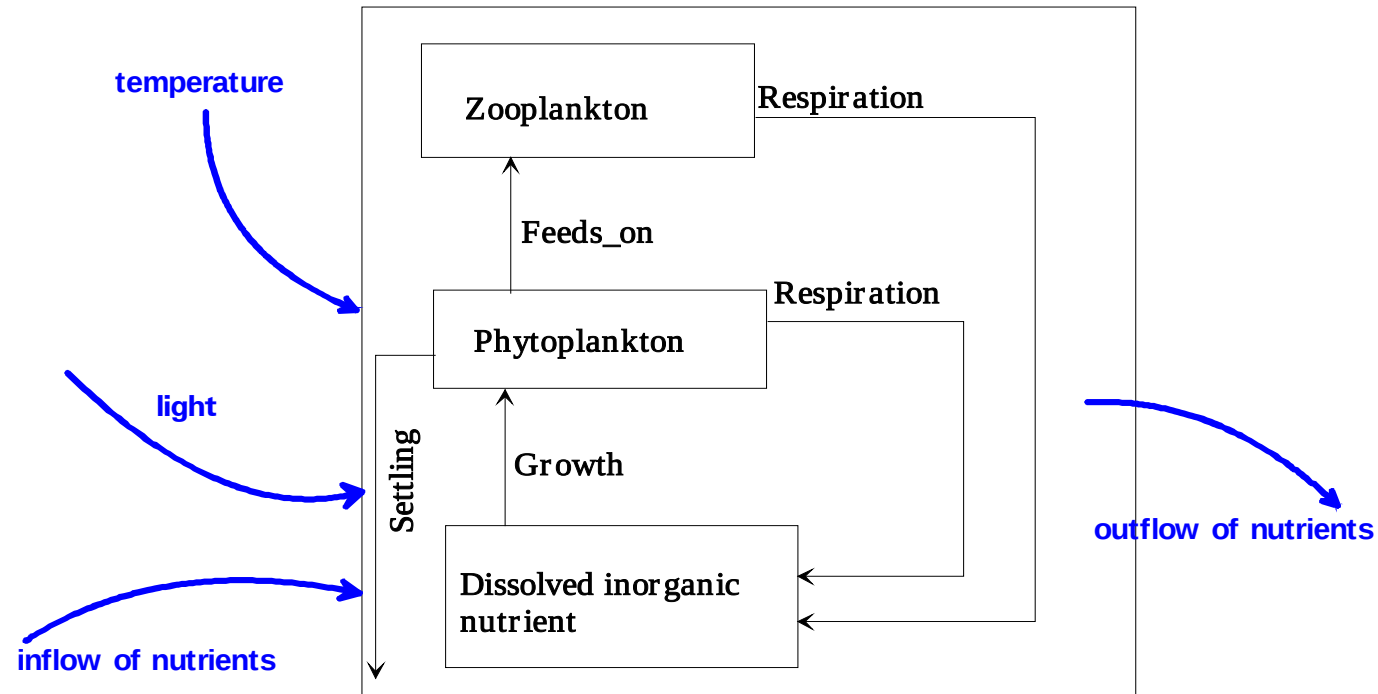


# LAKE GLUMSOE: EXPERIMENTS W/ PBM

|                         | Experiment 1                                | Experiment 2             |
|-------------------------|---------------------------------------------|--------------------------|
| system (state) variable | Chl-a                                       | Chl-a                    |
| independent variables   | temp, light, ps, no, zoo                    | temp, light, ps, no, zoo |
| training data           | Apr.73 to Apr.74                            | Oct.74 to Oct.75         |
| test data               | Oct.74 to Oct.75                            | Apr.73 to Apr.74         |
| goal(s)                 | discover and validate a phytoplankton model |                          |



# LAKE GLUMSOE: CONCEPTUAL DIAGRAM



# LAKE GLUMSOE: TASK SPECIFICATION

|     |                                                       |
|-----|-------------------------------------------------------|
|     | #Declaration of the variables in the system           |
| 1:  | variable Inorganic ns                                 |
| 2:  | variable Inorganic ps                                 |
| 3:  | system variable Primary_producer phyto                |
| 4:  | variable Animal zoo                                   |
| 5:  | variable Temperature temp                             |
| 6:  | variable Light light                                  |
|     | #Declaration of the processes in the system           |
| 7:  | process PP_growth(phyto, {ps,ns}, {temp}, {light}) p1 |
| 8:  | process Feeds_on(zoo, {phyto}, {temp}) p3             |
| 9:  | process Respiration_PP(phyto, {temp}, {}, {})         |
| 10: | process Sedimentation(phyto, {temp}) sed0             |



# LAKE GLUMSOE: RESULTS

- Model trained on 73/74 data

$$\begin{aligned} \frac{d\text{phyto}}{dt} = & \text{phyto} \cdot 0.5 \cdot \frac{ps}{ps + 0.009} \cdot \frac{\text{temp}}{20} \cdot \frac{\text{light}}{225.2} \cdot e^{-\left(\frac{\text{light}}{133.4} + 1\right)} - \text{phyto} \cdot 0.14 \cdot \frac{\text{temp} - 2.8}{20 - 4} \\ & - \text{phyto} \cdot \frac{0.28}{d} \cdot \frac{\text{temp} - 4}{20 - 4} - \text{zoo} \cdot 0.01 \cdot \frac{\text{temp}}{20} \cdot \frac{\text{phyto}}{\text{phyto} + 4.45} \cdot \text{phyto} \end{aligned}$$

- Model trained on 74/75 data

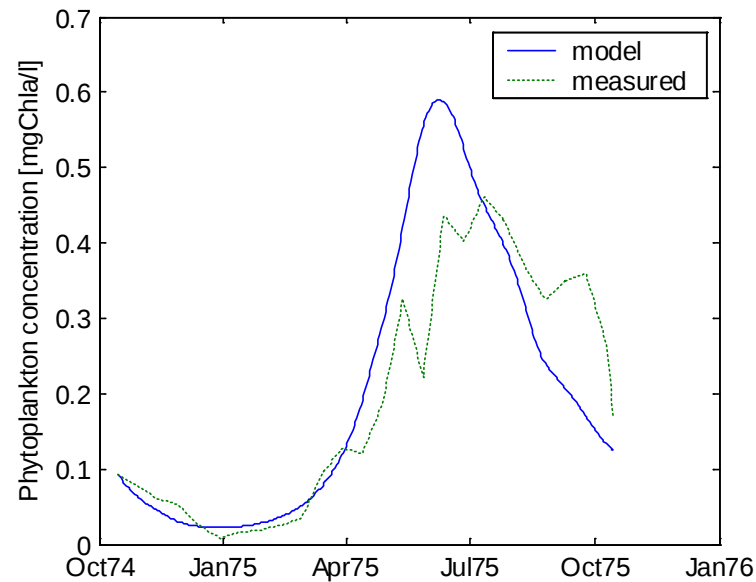
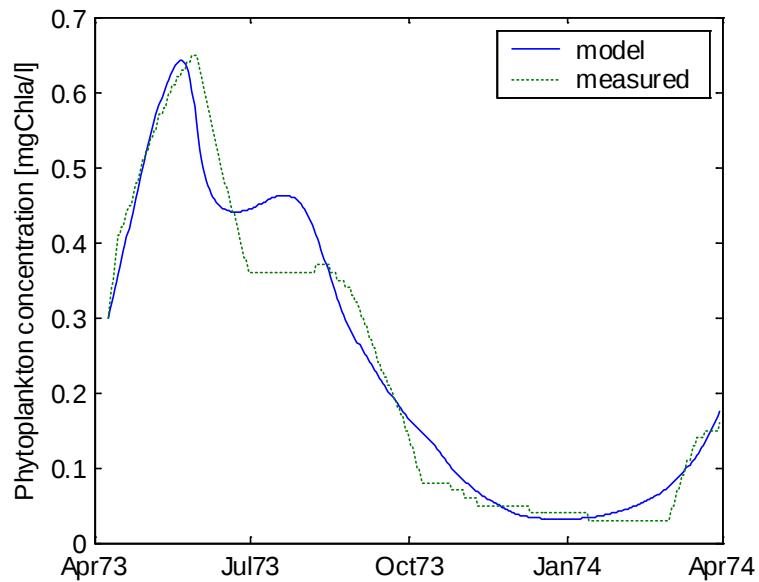
$$\begin{aligned} \frac{d\text{phyto}}{dt} = & \text{phyto} \cdot 0.25 \cdot \frac{ps^2}{ps^2 + 0.006} \cdot \frac{\text{temp}}{20} \cdot \frac{\text{light}}{151.9} e^{-\left(\frac{\text{light}}{135} + 1\right)} - \text{phyto} \cdot 0.12 \cdot \frac{\text{temp} - 4}{20 - 2} \\ & - \text{phyto} \cdot \frac{0.18}{d} \cdot \frac{\text{temp} - 2}{20 - 2.3} - \text{zoo} \cdot 0.01 \cdot 1.13^{(\text{temp} - 20)} \cdot \frac{\text{phyto}}{\text{phyto} + 5} \cdot \text{phyto} \end{aligned}$$



# LAKE GLUMSOE: RESULTS

Fit of the models to the training/testing data

- Left: Fit on training data (73/74)
- Right: Train 73/74, test 75/76





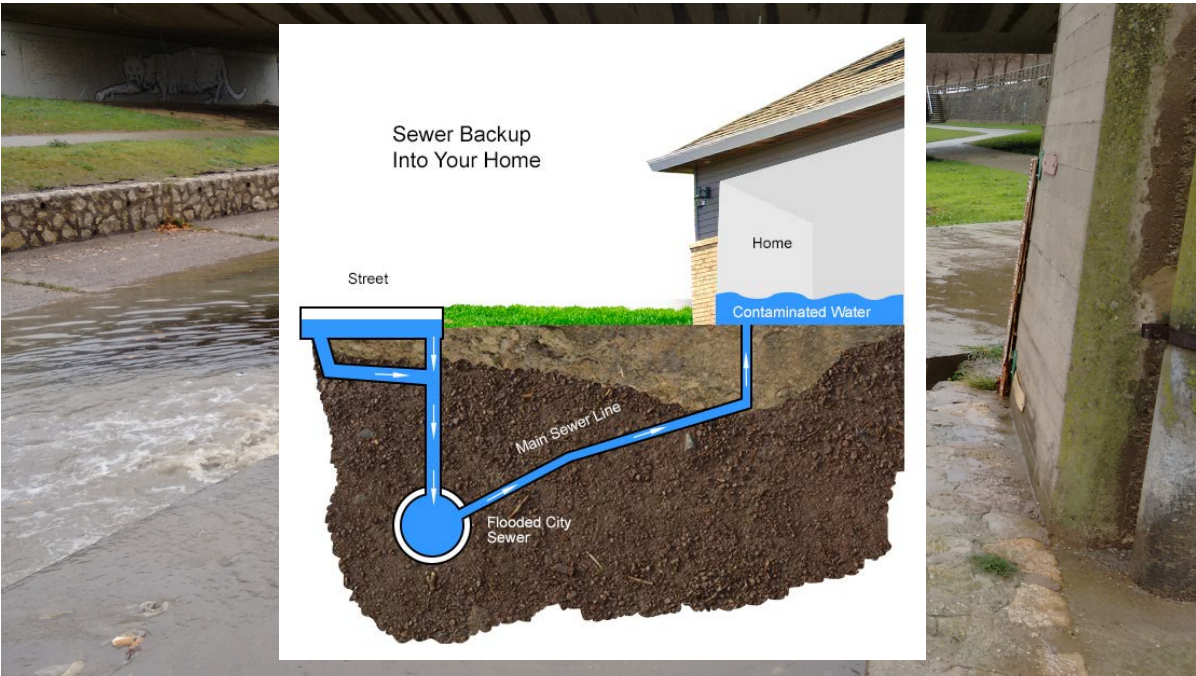
# MODELLING URBAN DRAINAGE

# MODELLING URBAN DRAINAGE: MOTIVATION

A major problem of urban drainage (UD) systems is the frequent overloading by stormwater:

- combined sewer overflows (CSOs) → pollution of recipients,
- road flooding, backwater.

The problem is made worse by climate change and urbanization.



# RESEARCH PROBLEM

Hydrology-hydraulic models (e.g. EPA-SWMM) are used:

- to analyze current state of urban drainage systems,
- for quantitative evaluation of different stormwater control measure scenarios.
- Typically:
- only one mathematical model (predetermined by the modeller) is used to describe a single (hydrological) process within the urban catchment,
- calibration is performed either manually or by employing search techniques (e.g., genetic algorithms, neural networks)

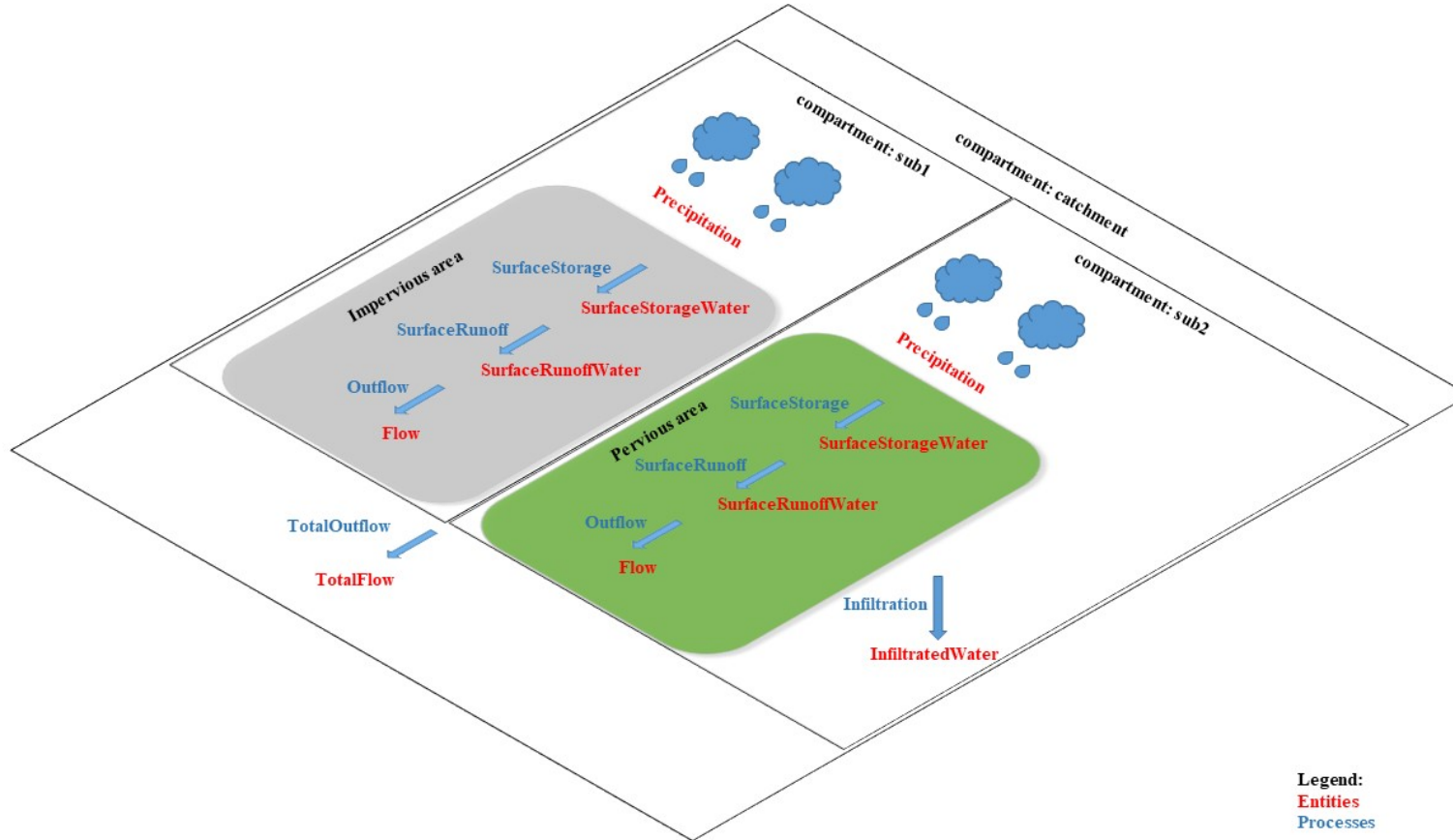
## Goal:

- among multiple alternatives find the mathematical model most suitable for describing the selected (UD) processes and
- calibrate the model parameters on the measured flow data.



# CONCEPTUAL MODEL (WATER QUANTITY)

- Modeled urban catchment divided into impervious and pervious area, forming a tree like structure of compartments.



# COMPONENTS LIBRARY (PROCESSES AND ENTITIES)

//Compartments

**template compartment** SpatialUnit {

**entities:**

Water,  
Precipitation,  
CumulativePrecipitation1,  
CumulativePrecipitation2,  
InfiltratedWater,  
SurfaceRunoffWater,  
SurfaceStorageWater,  
Flow,  
TotalFlow,  
Surface;

**processes:**

Infiltration,  
InfiltrationSCS,  
InfiltrationUKWIR,  
InfiltrationVARUK,  
SurfaceRunoff,  
SurfaceStorage,  
Outflow,  
TotalOutflow;

**compartments:**

SpatialUnit;

}

// Surface

**template entity Surface** {

**consts:**

area {range:<0,inf>; unit:"m2"},  
slope {range:<0,1>; unit:"m/m"},  
CN {range:<30,99>},  
width{range:<100,20000>; unit:"m"},  
depstordepth {range:<0.00005,0.01>;  
unit:"m"},

n {range:<0.01,0.8>},  
PIMPimp {range:<0,100>},  
IF {range:<0.5,1>},  
B {range:<0.5,0.8>},  
Plimp {range:<0,5>},  
PFimp {range:<10,50>; unit:"mm"},  
PIMPp {range:<0,100>},  
NAPI {range:<0,40>},  
Plp {range:<0.7,0.9>},  
Cr {range:<0.8,1.0>},  
SPR {range:<0.1,0.7>},  
PFp {range:<30,100>; unit:"mm"};

}



# ALTERNATIVE INFILTRATION MODELS

```
// Processes
// Hydrological processes
template process Infiltration (cprec1 : CumulativePrecipitation1, cprec2 :
CumulativePrecipitation2, surf : Surface, prec: Precipitation, infil : InfiltratedWater)
{}
template process InfiltrationSCS: Infiltration {
    equations:
    infil.amountOfWater = ...;}
template process InfiltrationVARUK: Infiltration {
    equations:
    infil.amountOfWater = ...;}
template process InfiltrationUKWIR: Infiltration {
    equations:
    infil.amountOfWater = ...;}
```



# CASE STUDY: LJUBLJANA

- Area: 17.5 ha; Terrain slope: 2.7°
- Land use: single-family houses with gardens
- 5.4 km of combined sewer system
- Rain gauge: Davis® (0.2 mm) Rain Gauge Smart Sensor
- Flow calculated based on a combination of non-contact radar velocity measurements and ultrasonic level measurements



# MODEL CALIBRATION

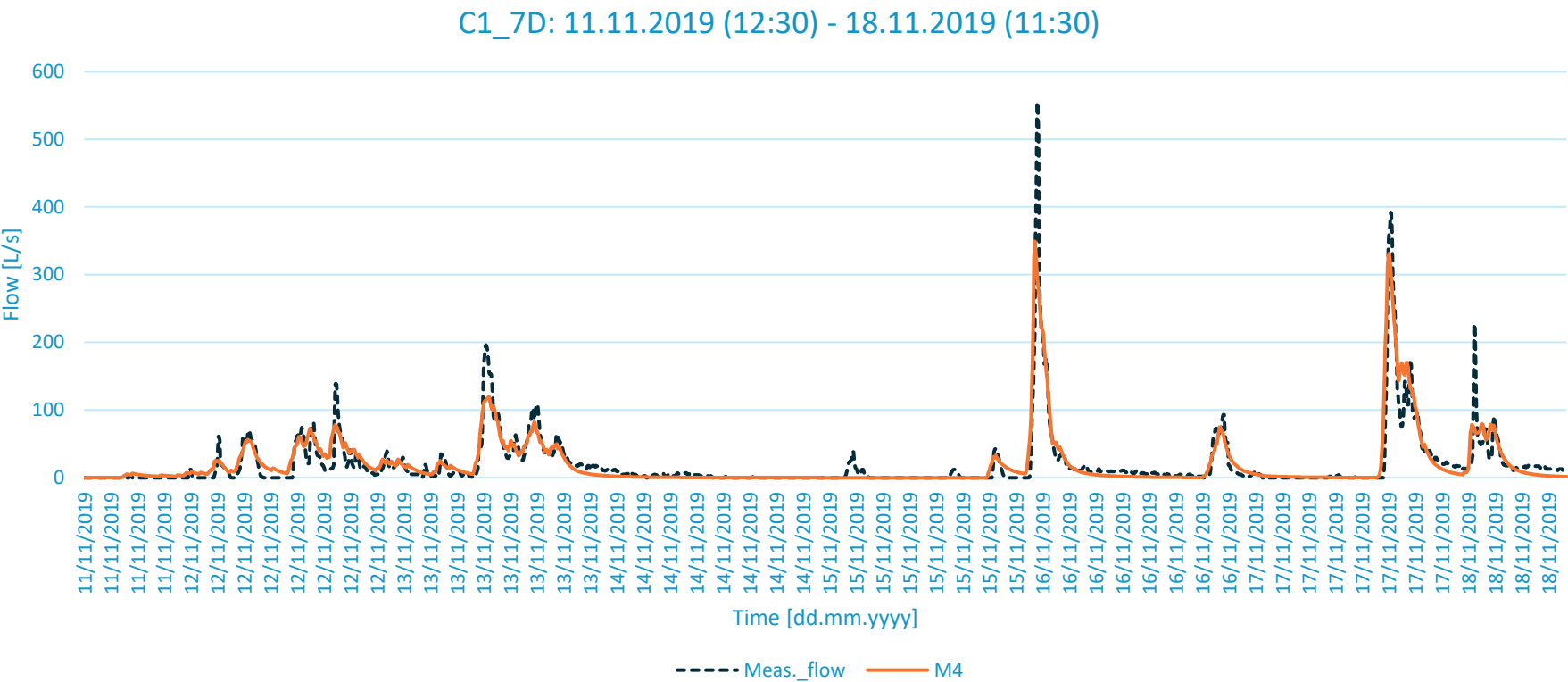
NSE (Nash-Sutcliffe efficiency coefficient) used to evaluate the “goodness-of-fit” of hydrological models.

1: a perfect match between observed and modelled discharge

0: the observed mean is as good predictor as the model

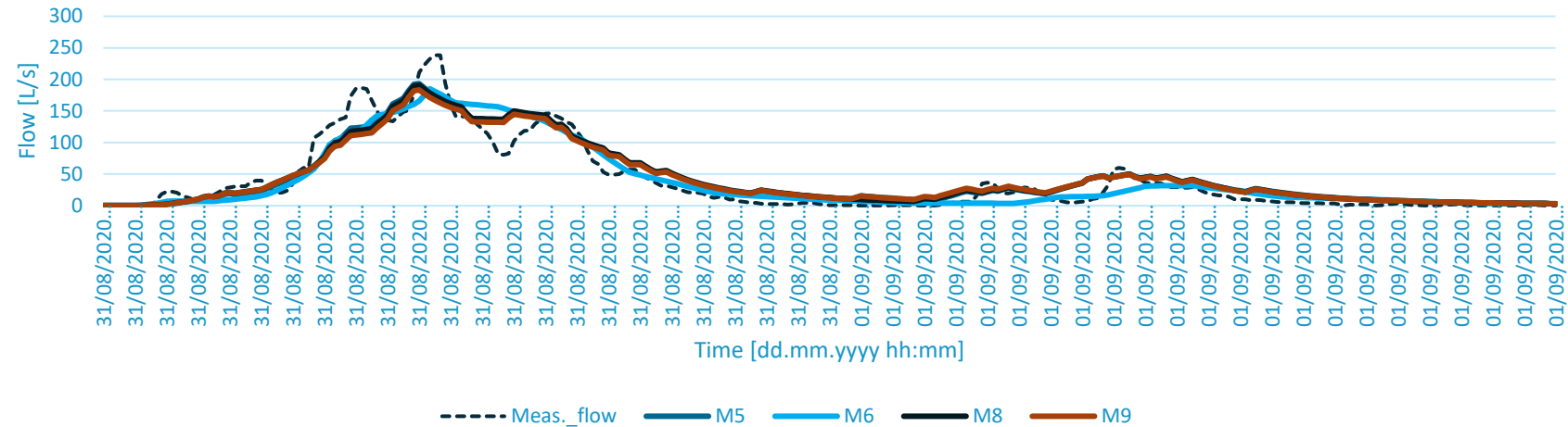
<0: the observed mean is a better predictor than the model

| Model   | Infil Sub 1 | Infil Sub 2 | NSE  | RMSE [L/s] |
|---------|-------------|-------------|------|------------|
| M1      | SCS         | SCS         | 0.82 | 16.24      |
| M2      | UKWIR       | SCS         | 0.82 | 15.78      |
| M3      | VARUK       | SCS         | 0.82 | 15.58      |
| M4      | UKWIR       | SCS         | 0.83 | 15.14      |
| M5      | UKWIR       | UKWIR       | 0.83 | 15.63      |
| M6      | VARUK       | UKWIR       | 0.82 | 16.04      |
| M7      | SCS         | VARUK       | 0.83 | 15.26      |
| M8      | UKWIR       | VARUK       | 0.82 | 16.14      |
| M9      | VARUK       | VARUK       | 0.82 | 15.47      |
| AVERAGE |             |             | 0.82 | 15.70      |

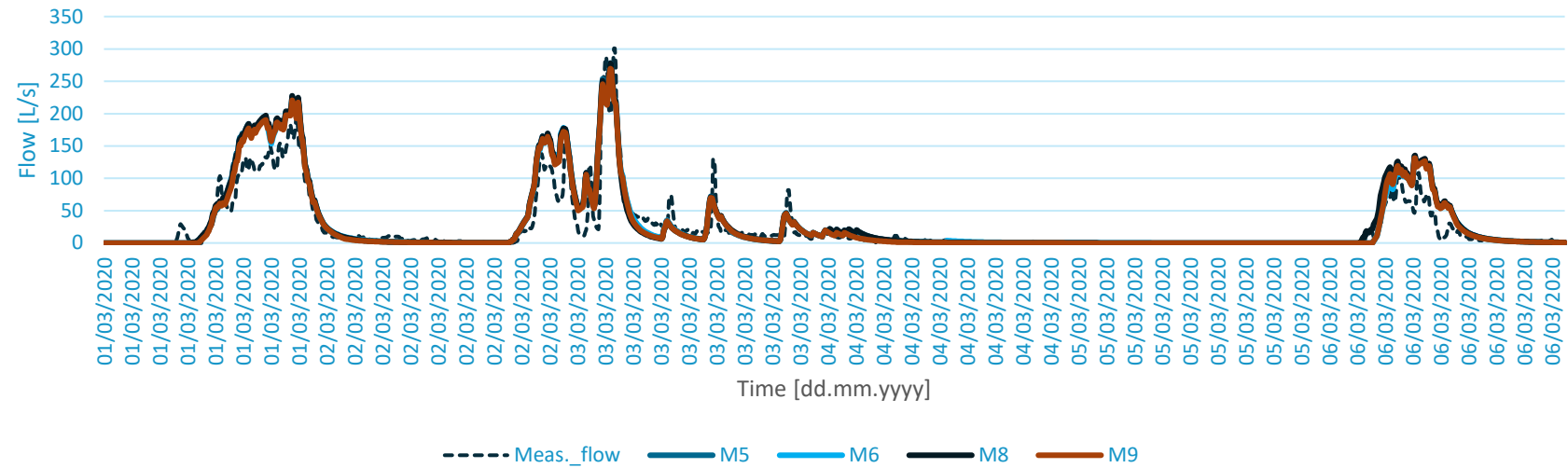


# MODEL VALIDATION

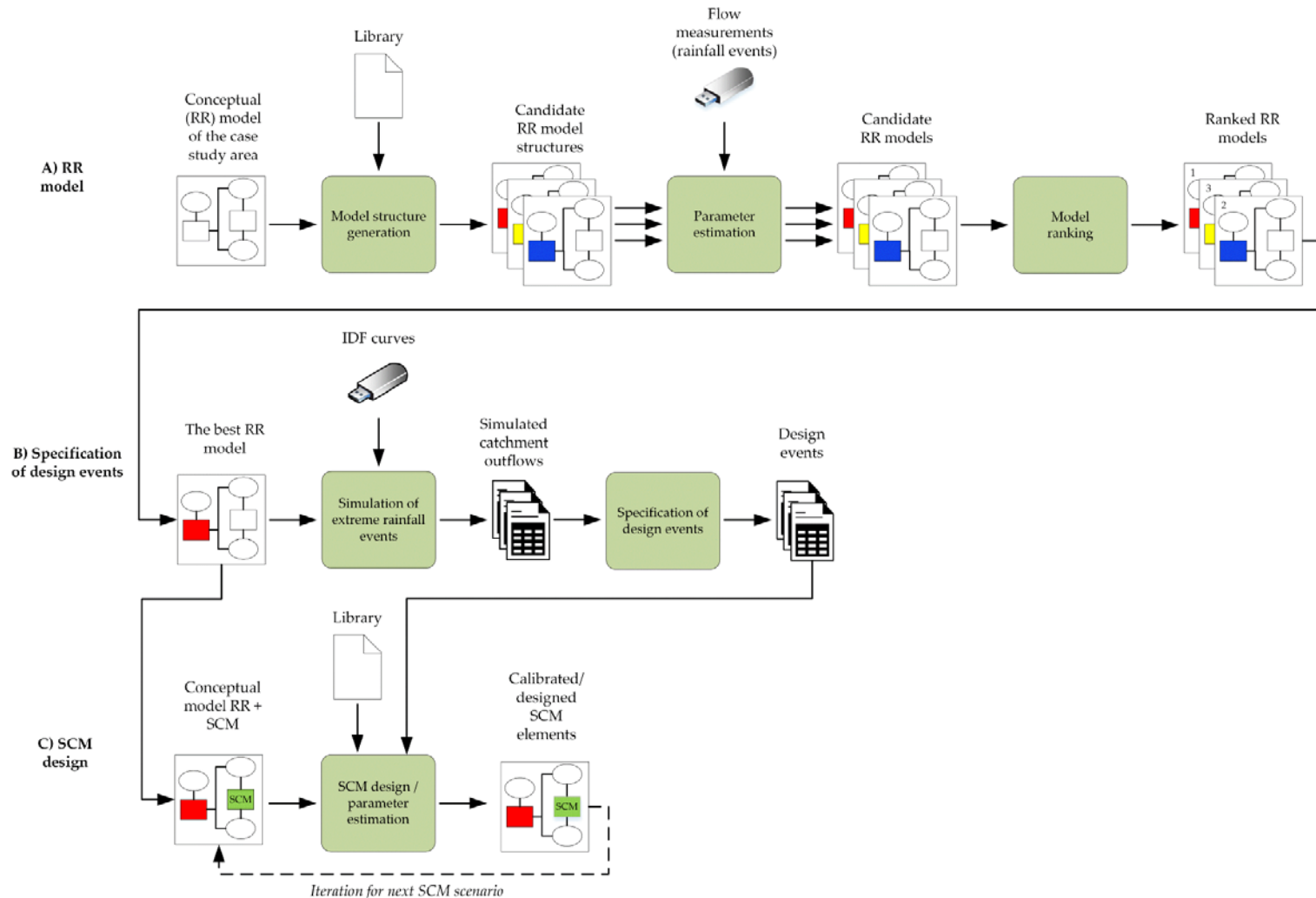
V2\_1D: 31.8.2020 (12:00) - 1.9.2020 (11:00)



V5\_5D: 1.3.2020 (03:40) - 6.3.2020 (23:35)



# DESIGN OF STORMWATER CONTROL MSRS



*A schematic workflow for the rainfall-runoff (RR) model discovery and stormwater control measure (SCM) design using the automated modelling tool ProBMoT.*

