Application of Neuro-Fuzzy Techniques to Predict Ground Water Vulnerability

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Introduction

- There is a need to develop new modeling techniques that assess ground water vulnerability with less expensive data and robust when data are uncertain and incomplete.

Objectives

- Loosely couple Neuro-fuzzy techniques and GIS to predict ground water vulnerability in a relatively large watershed
- Examine the sensitivity of the Neuro-fuzzy models by changing training parameters
- Determine the effects of the size of the training data sets on model predictions

Software

- NEFCLASS-J (Neuro-fuzzy software in JAVA)
- GRASS (GIS software in C)

Characteristics of the Model(s)

- Capability to deal with uncertainties
- Tolerate imprecision
- Extract information from incomplete data sets
- Incorporate expert's opinion directly into the model
- Regional Scale
- The models use existing data bases
- Integrated in a GIS

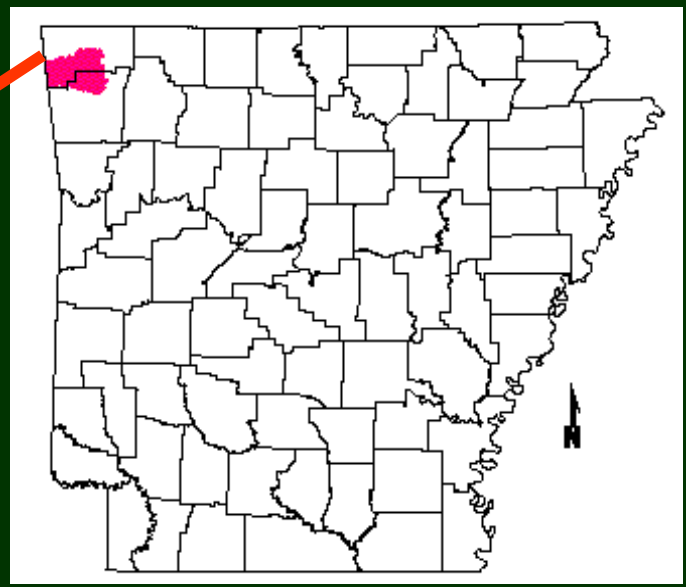
Why hybrid?

- Schultz and Wieland (1997) suggested that NN could parsimoniously represent non-linear systems and seem to be robust and flexible under data driven situations and allow deeper professional insight into the model.
- Fuzzy logic provides an opportunity to incorporate experts' opinion and robust under uncertainty.

Assessment of Models

- Comparison of models and field data
  - Coincidence analyses

Location of the Study Area



Sources of Primary Data

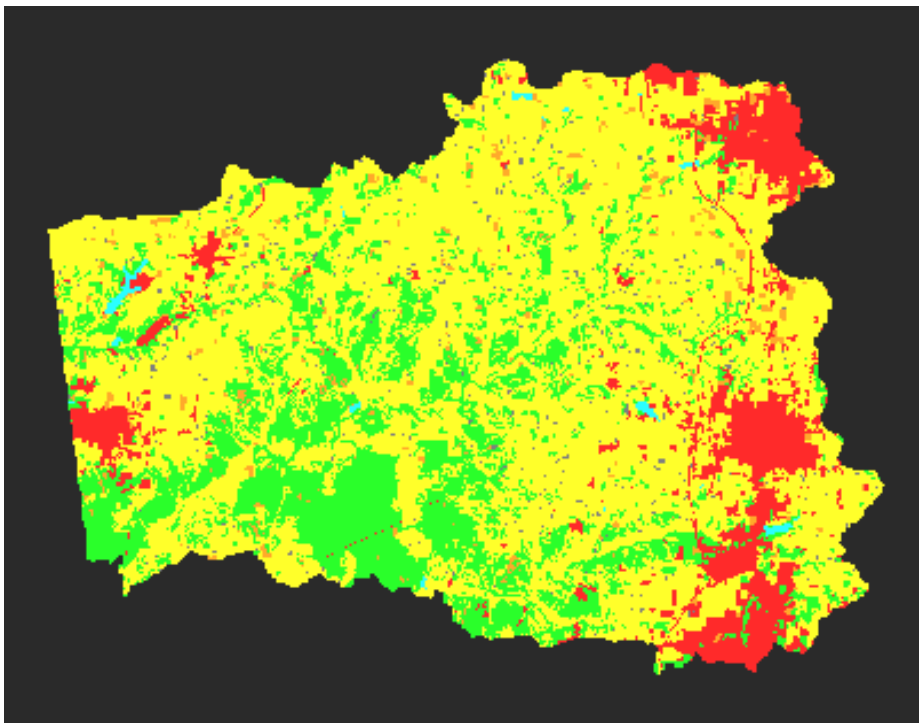
- Soils (USDA - NRCS; 1:24,000)
- Landuse (USGS; Landsat TM - 30m)

USDA-NRCS: US Dept. of Agriculture – Natural Resources Conservation Services
USGS: US Geological Survey

Model Inputs

- Soil Structure
- Depth of the Soil Profile
- Soil Hydrologic Group
- Landuse

Input Parameter: Landuse



Urban

Agriculture

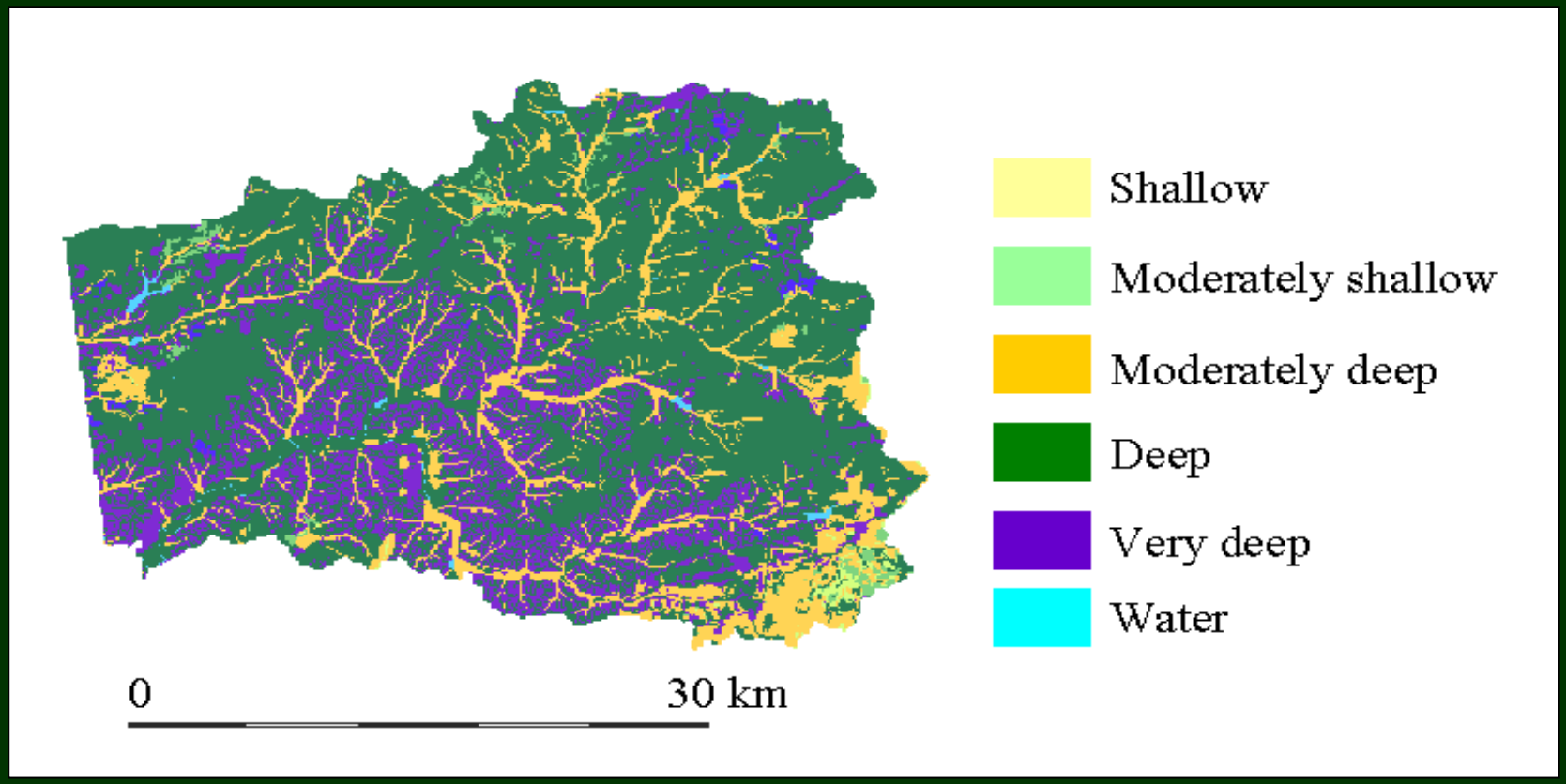
Forest

Brush and shrubs

Water

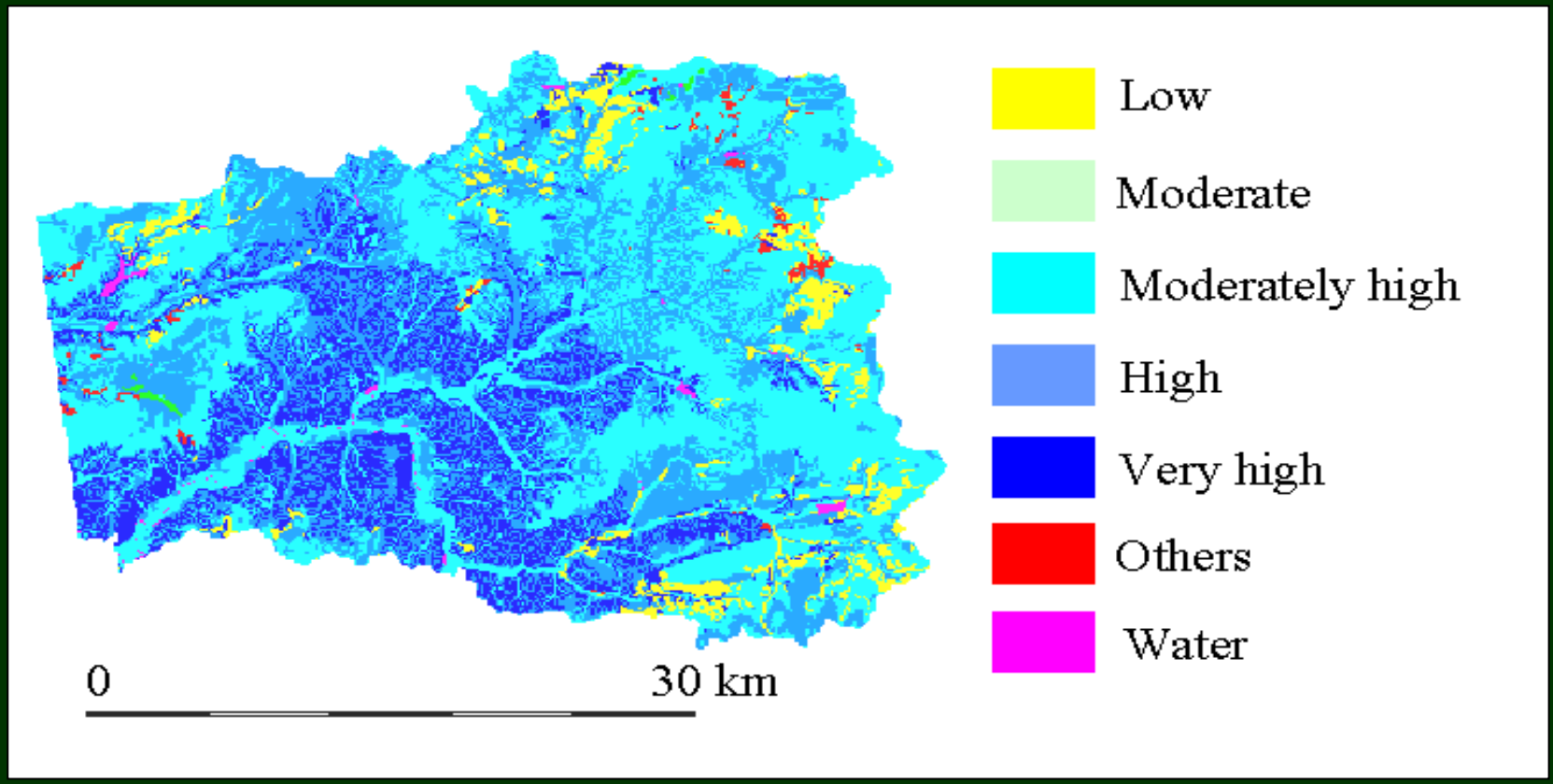
0 30 km

Input Parameter: Depth of the Soil Profile



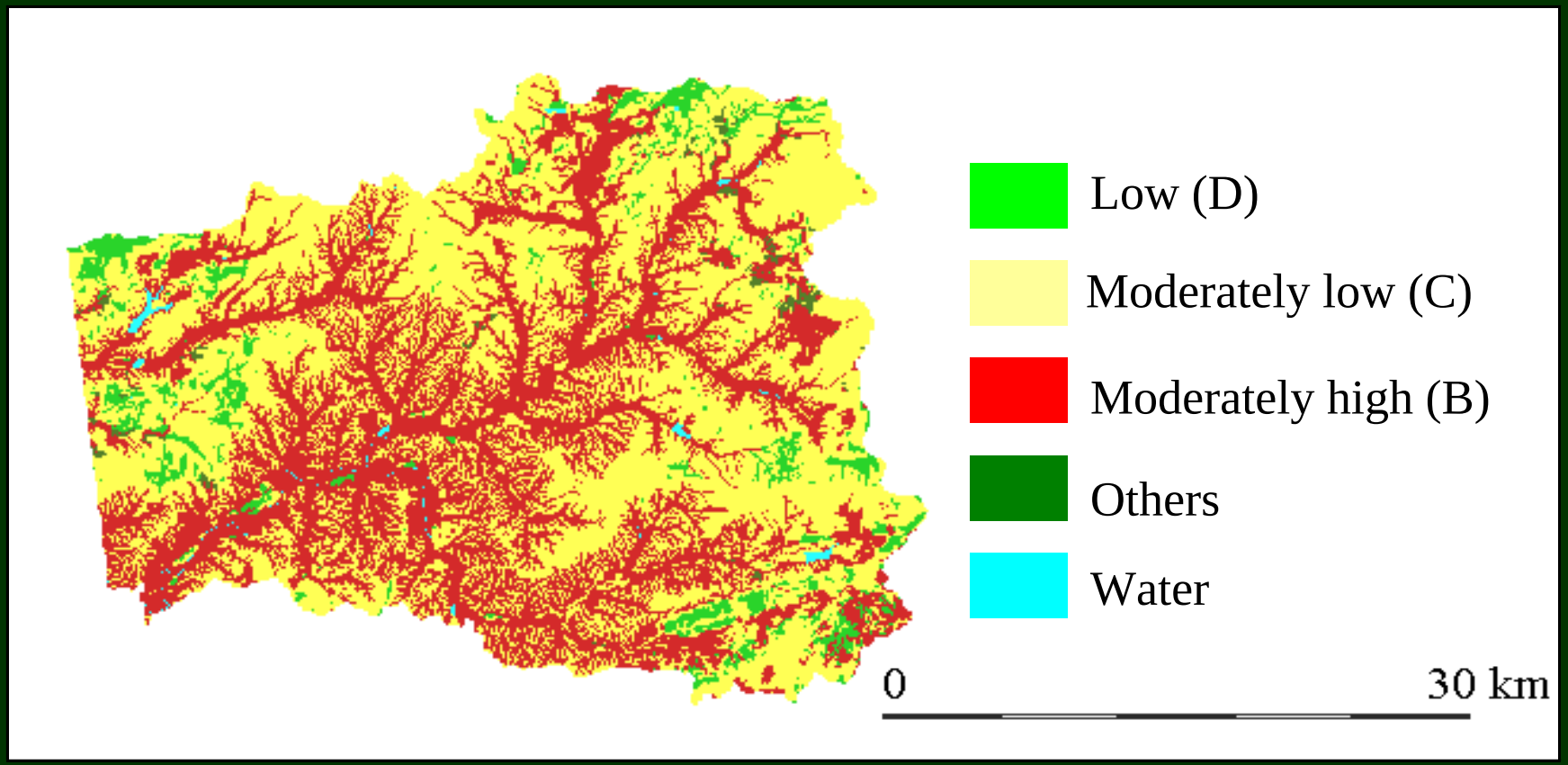
Shallow: 23- 76 cm, moderately shallow: 77 – 127 cm, moderate: 128-175 cm, deep: 176 – 215 cm, and very deep: > 216 cm

Input Parameter: Soil Structure

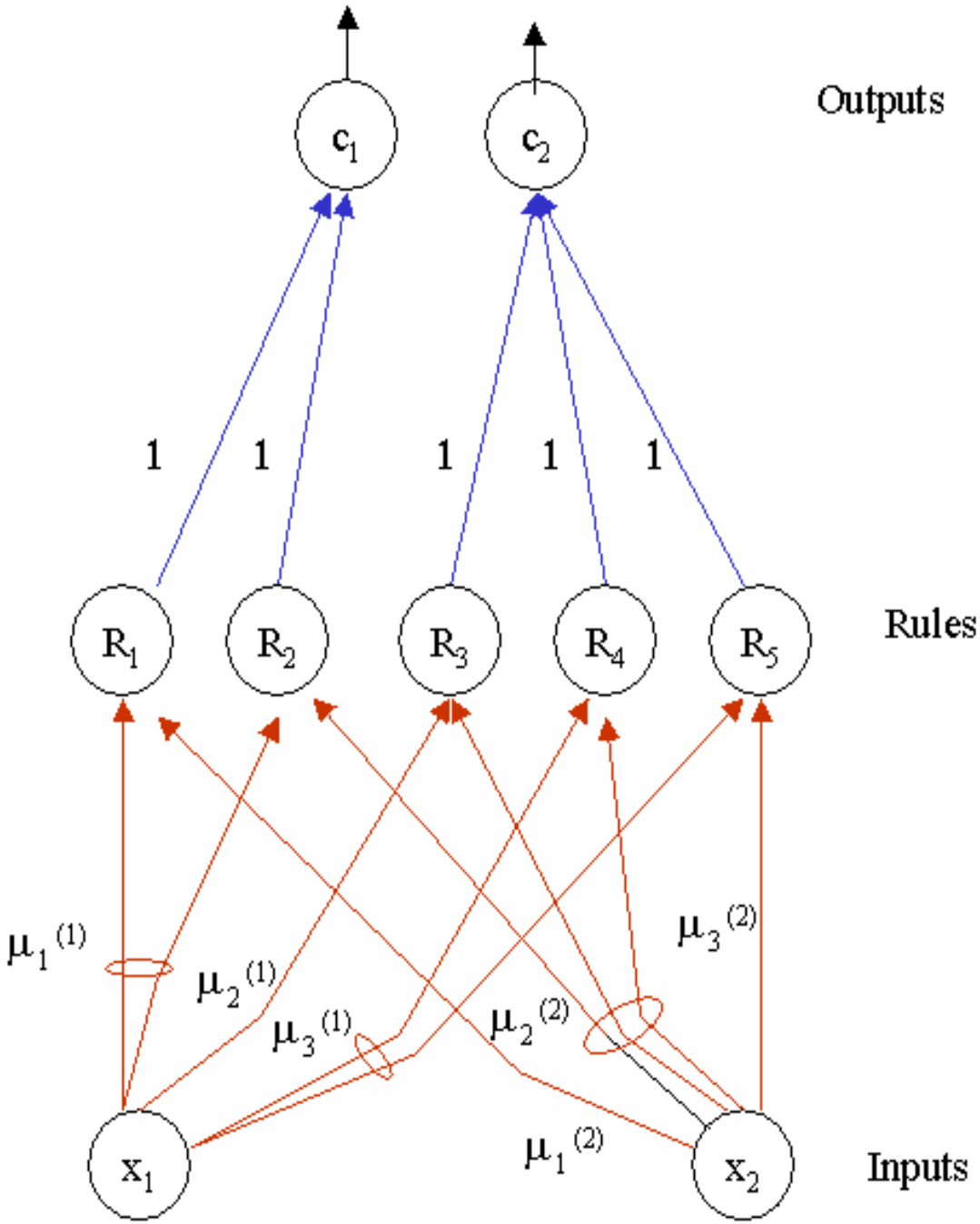


Pedality Points. Low: 10 – 17, moderate: 18- 30, moderately high: 31 – 40, high: 41 – 50, and very high > 51.

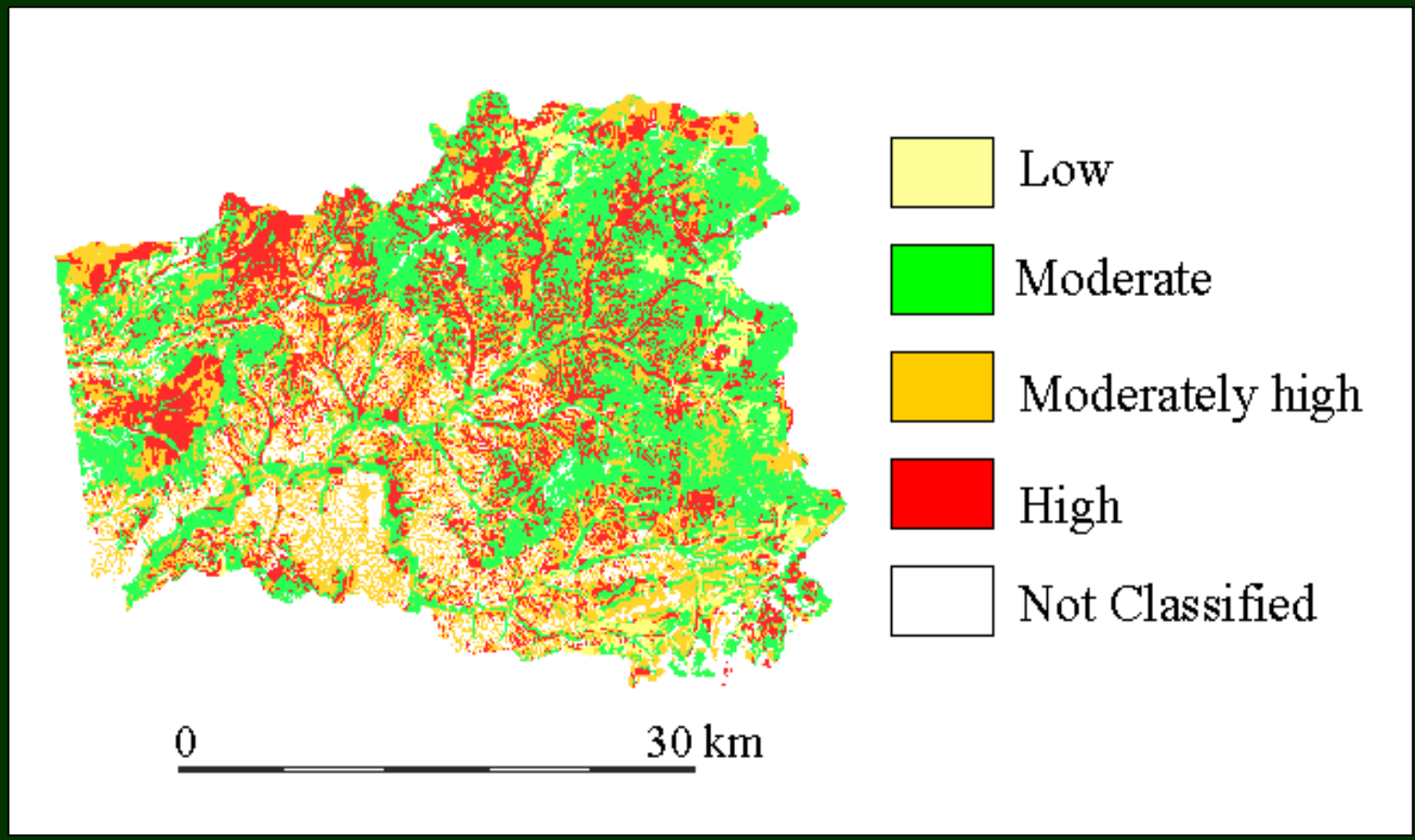
Input Parameter: Soil Hydrologic Group



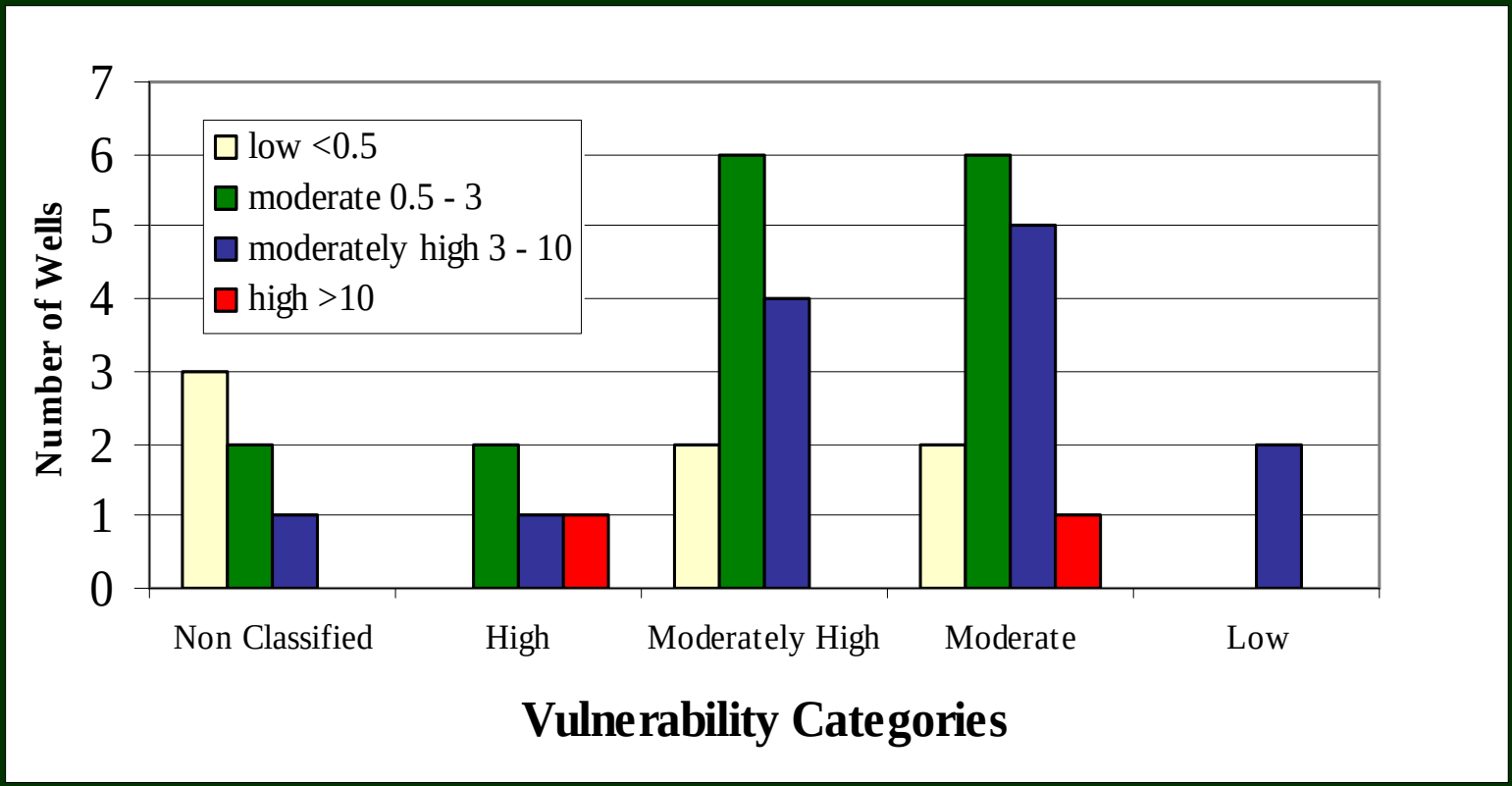
Neuro-Fuzzy Model



Spatial Distribution of Vulnerability from the Objective 1

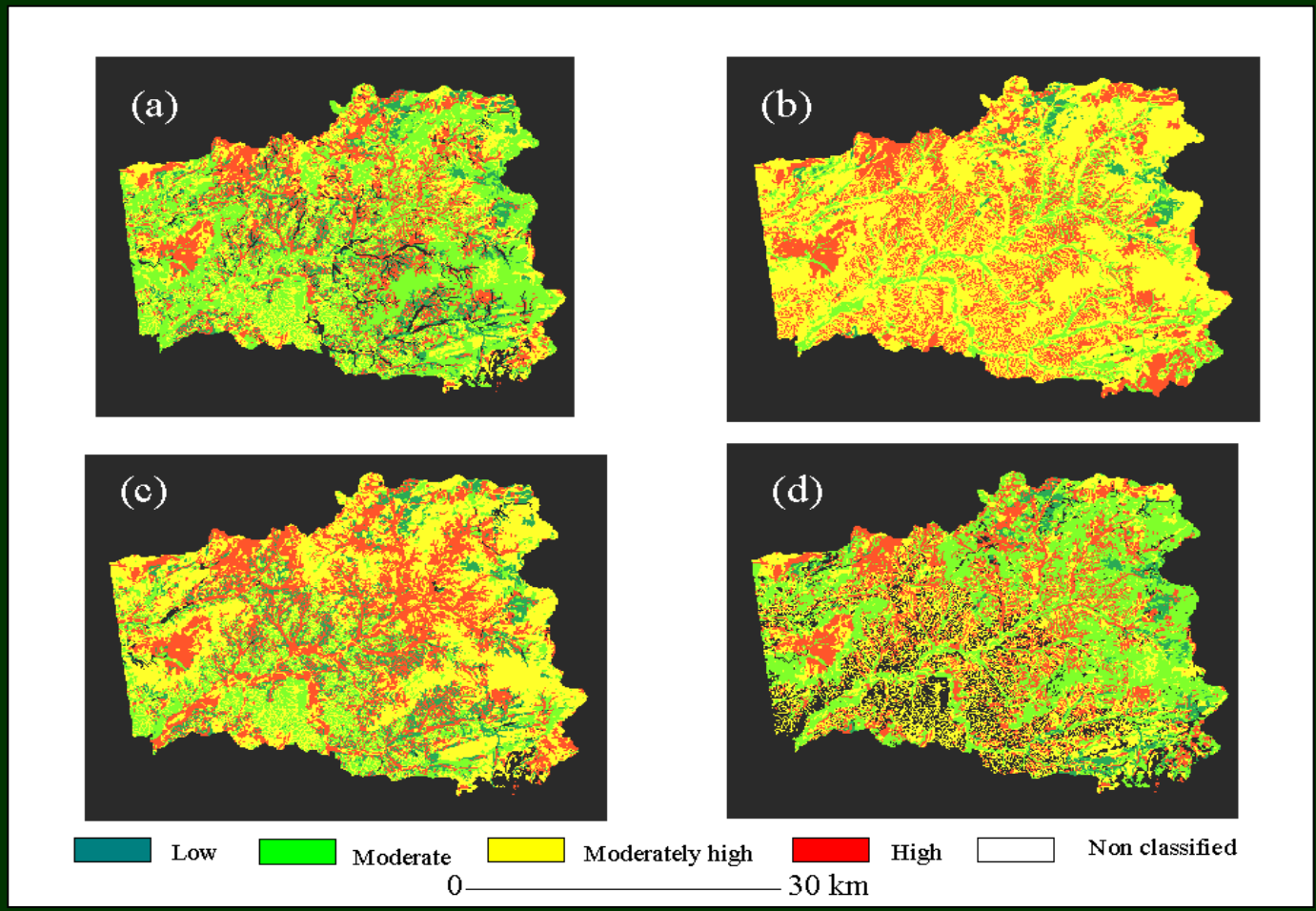


Coincidence between Well Contamination Data and Vulnerability Categories



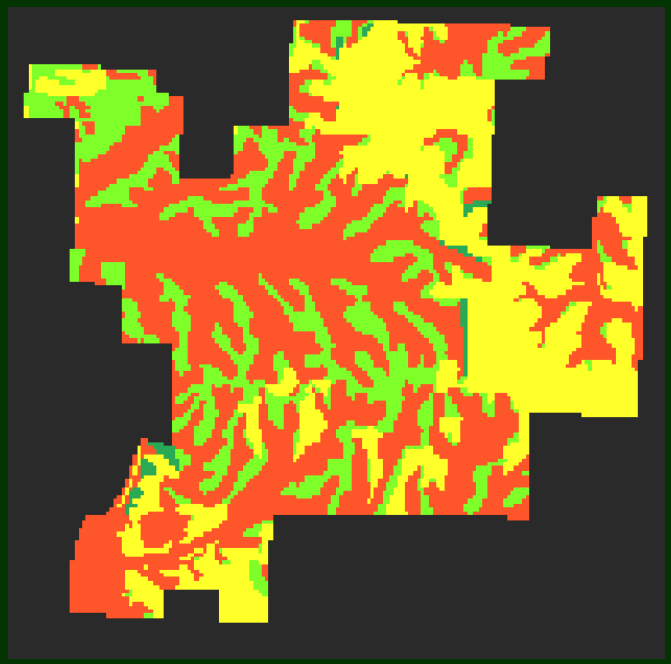
Nitrate-N mg/l

Objective 2: Sensitivity Analysis



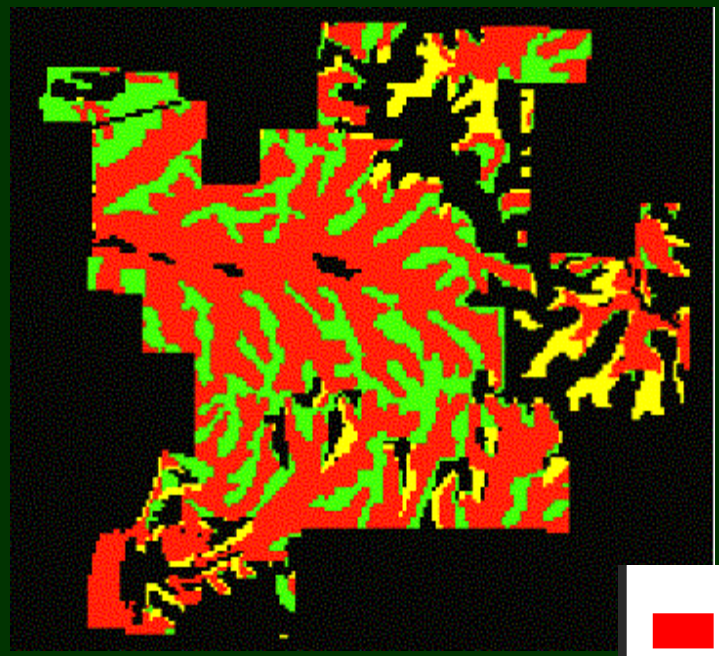
Spatial distribution of ground water vulnerability generated by objective 2. (a) Model-1, (b) Model-4, (c) Model-8, (d) Model-14

Objective 3: Size of the Training Data Sets Vs. Neuro-fuzzy Models



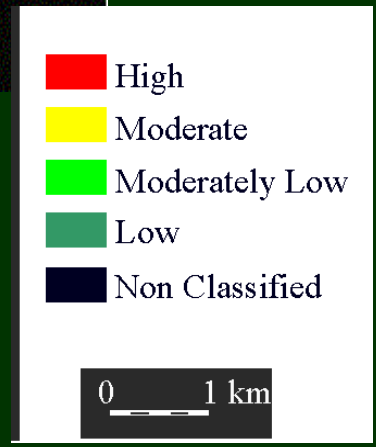
a) Model1_savoy,

Field to Field

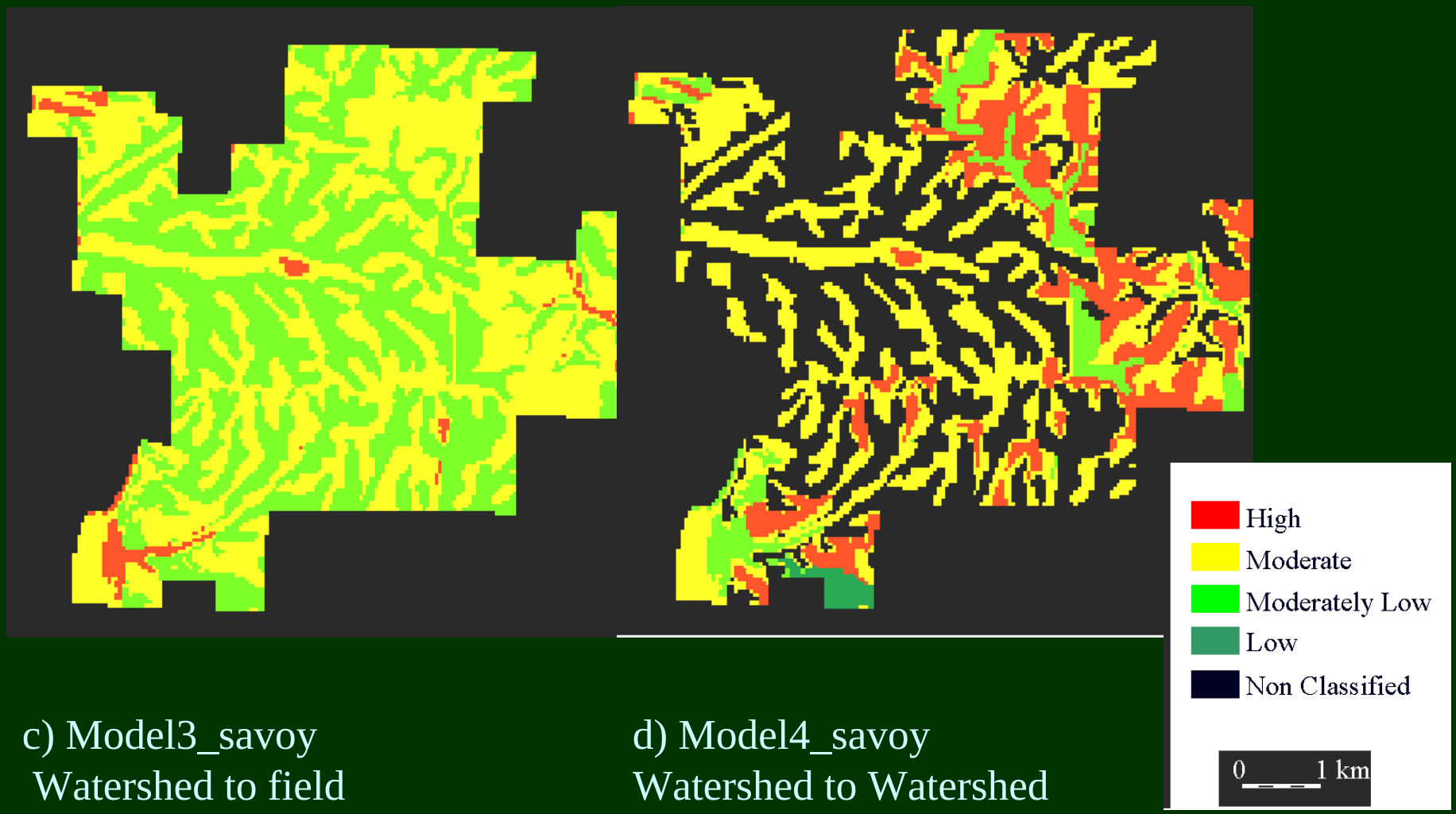


b) Model2_savoy,

Field to Watershed



Objective 3: Size of the Training Data Sets vs. Neuro-fuzzy Models



c) Model3_savoy
Watershed to field

d) Model4_savoy
Watershed to Watershed

Conclusions

- Sensitivity analyses conducted by varying parameters of the models indicated that the Neuro-fuzzy systems are sensitive to the parameters used during the training processes and size of the training data.
- Vulnerability map generated by Model-8 with trapezoidal sets and no rule weights showed higher coincidence with well contamination data.

Conclusions cont..

- Transfer of SEW to the watershed scale models resulted in greater area in the non-classified category.
- Size of the training data and number of unique combinations represented in the training data set influenced the training.
- Models trained with inappropriate training and application data resulted meaning less coincidence between vulnerability categories and well data.

Conclusions cont..

- From this research it is evident that the Neuro-fuzzy technique has the potential in facilitating modeling ground water vulnerability at a regional scale but would require modifications for wider ranges of application.

Future Direction

- Use larger number of wells and water quality data to determine meaningful relations between predicted vulnerability classes and well contamination
- In the future, vulnerability maps should be generated from multiple approaches such as NN, Fuzzy Logic, Neuro-fuzzy and Geostatistics and all of these maps should be compared in a GIS to identify ground water vulnerable zones.

Input Parameter: Soil Series