Prediction of rainfall-generated soil erosion processes with artificial neural networks and GIS using advangeo®

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Geo-Network of Latinamerican-German Alumni

Agenda

- **Theoretical Background: Artificial Intelligence / Artificial Neural Networks**
- **Short Presentation of Developed Software advangeo®**
- **Description of Work Methodology:**
  - Case Study 1 - Erosion Vulnerability: Extensive Soil Erosion, Klingenberg (Germany)
  - Case Study 2 - Erosion Vulnerability: Erosion Gullies, Limpopo (South Africa)
- **Conclusion**
- **Further Case Studies**
- **Summary**
- **References**

Motivation

Where are the deposits located ?

Where do forest pests spread ?

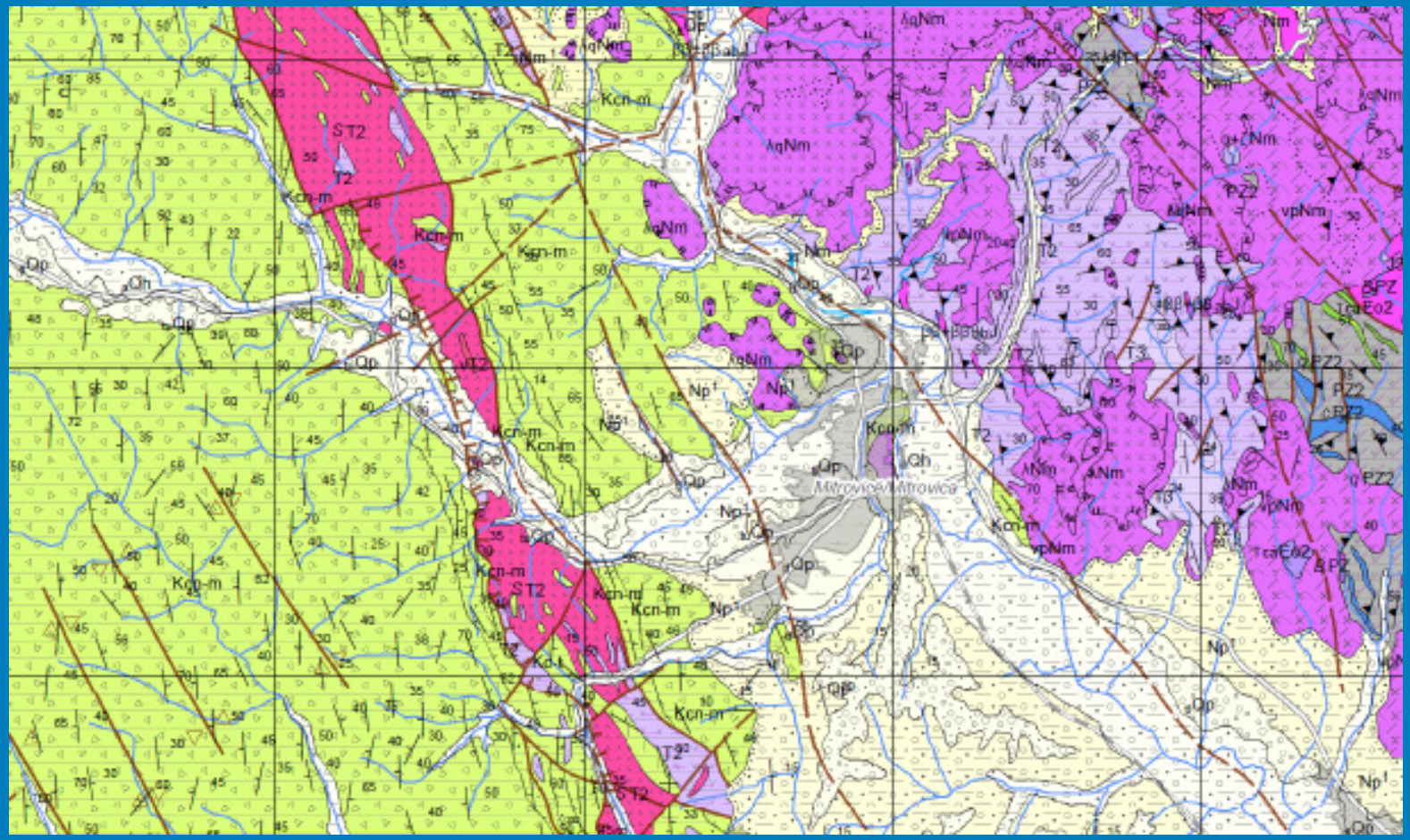
Motivation

Where does coal burn ?

Where are karst caves located ?

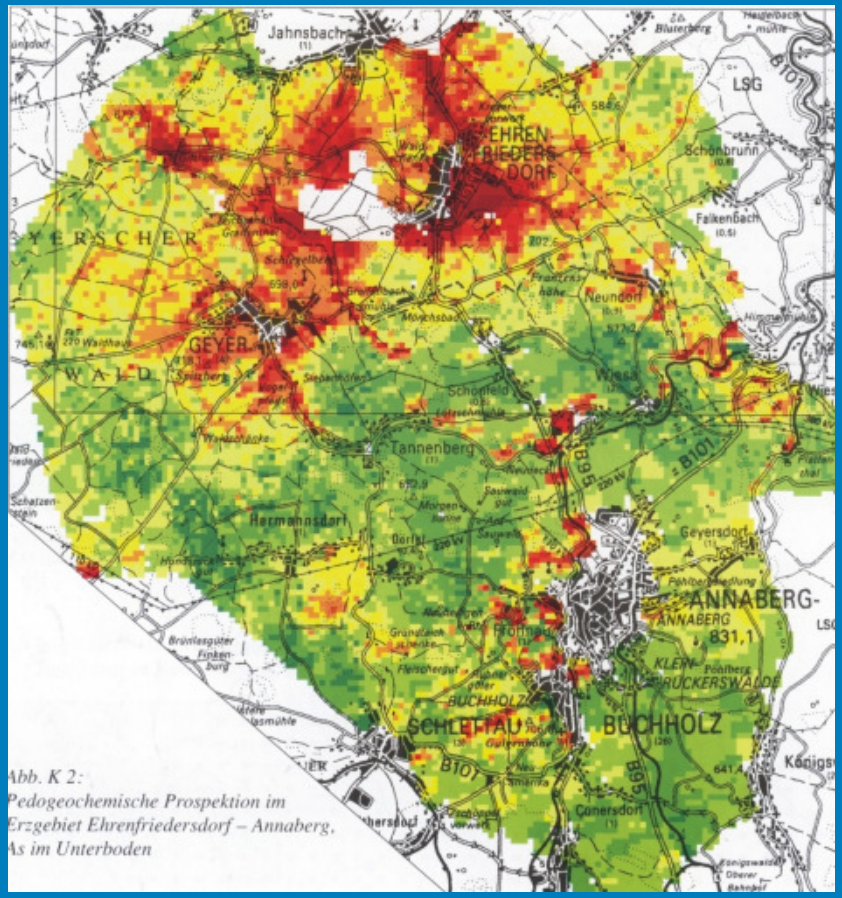
Motivation

Where is a geological / pedological boundary?



Motivation

Where is soil contaminated ?

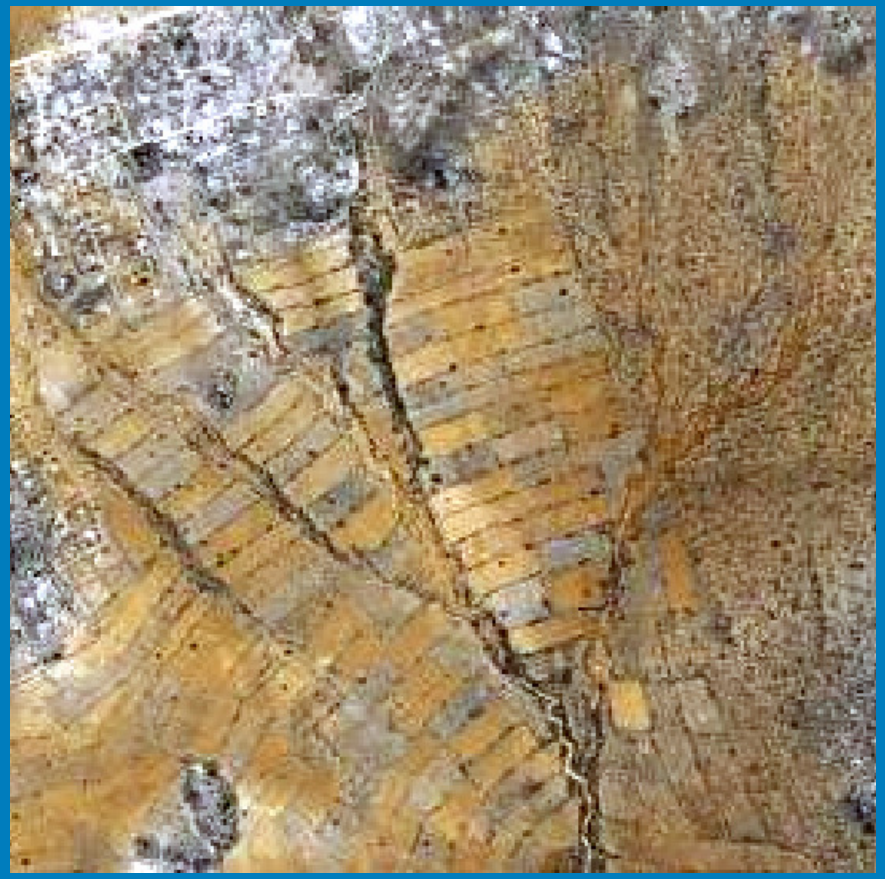


Quelle: LfULG Sachsen

Motivation

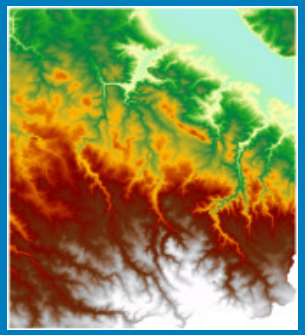
Where does the hillside slide?

Where do erosion gullies form?

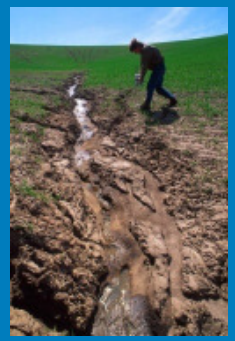


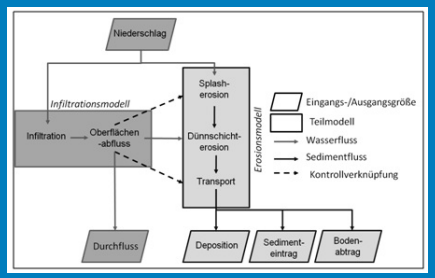
Working Steps for Data Analysis

Input Data:
Soil Types, Surface Characteristics, Landuse

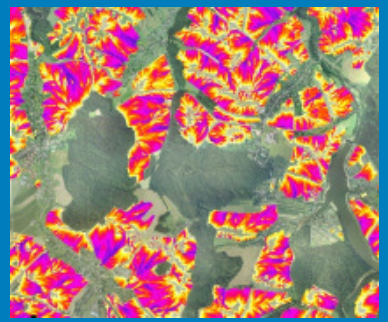


Knowledge:
Known Events, Relationships



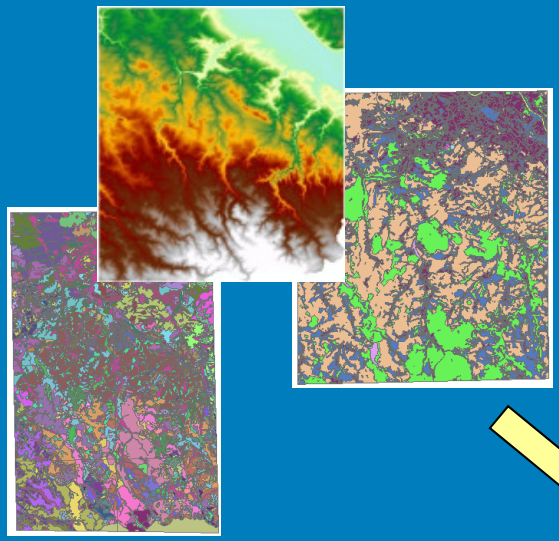


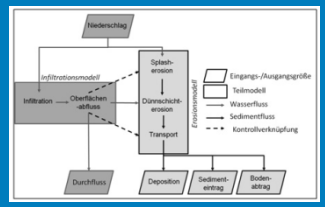
Possibilities of Data Analysis:
Analytical or Empirical / Statistical Approaches



Application of Training→ Prediction Maps

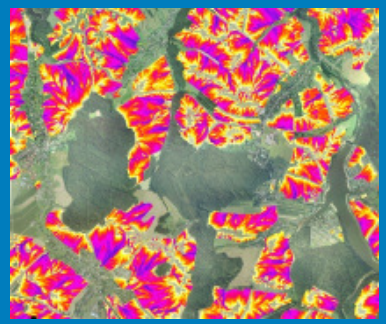
Traditional Approach



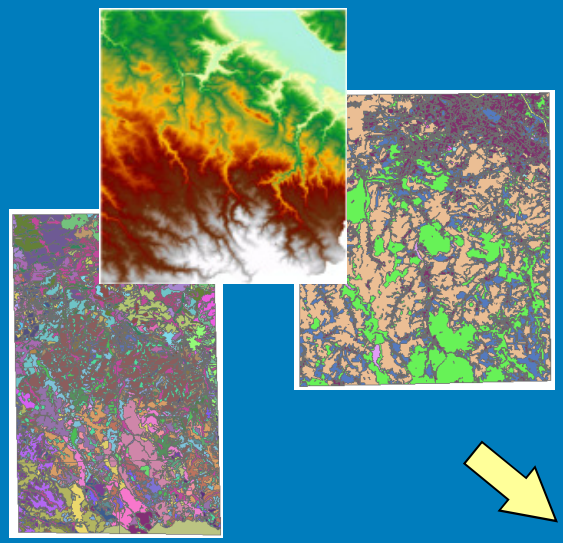


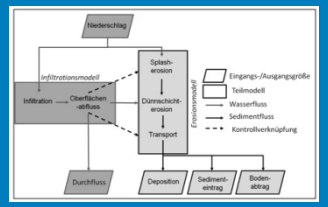
Traditional prediction methods are based mainly on the expert´s knowledge / experience supported by modern information technology

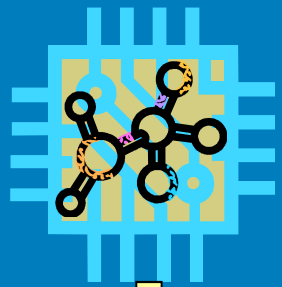
Data Analysis and Interpretation

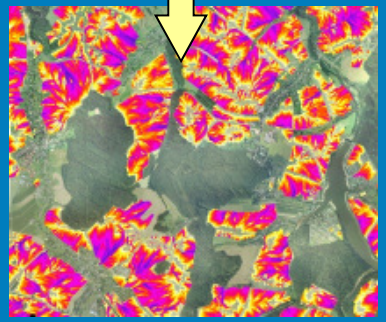


Modern Approach Using Artificial Intelligence







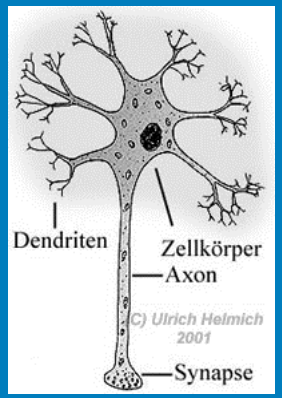


Pre-Processing

Validation

The artificial neuronal network "replaces" the experts empirical data analysis

Definition: Artificial Neural Networks

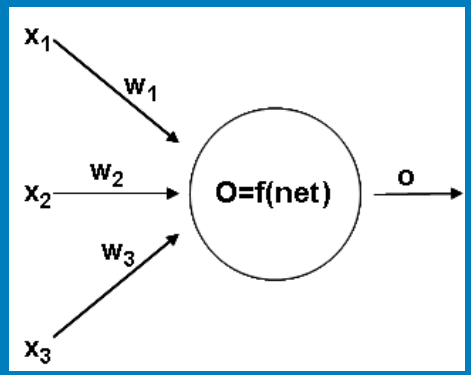


Modell: Neuron Cell

- Functionality as a biological neural system
- Consists of artificial neuron cells
- Simulation of biological processes of neurons by use of suitable mathematical operations
- In most cases layer-like configuration of the neurons

The Neuron Cell as a Processor

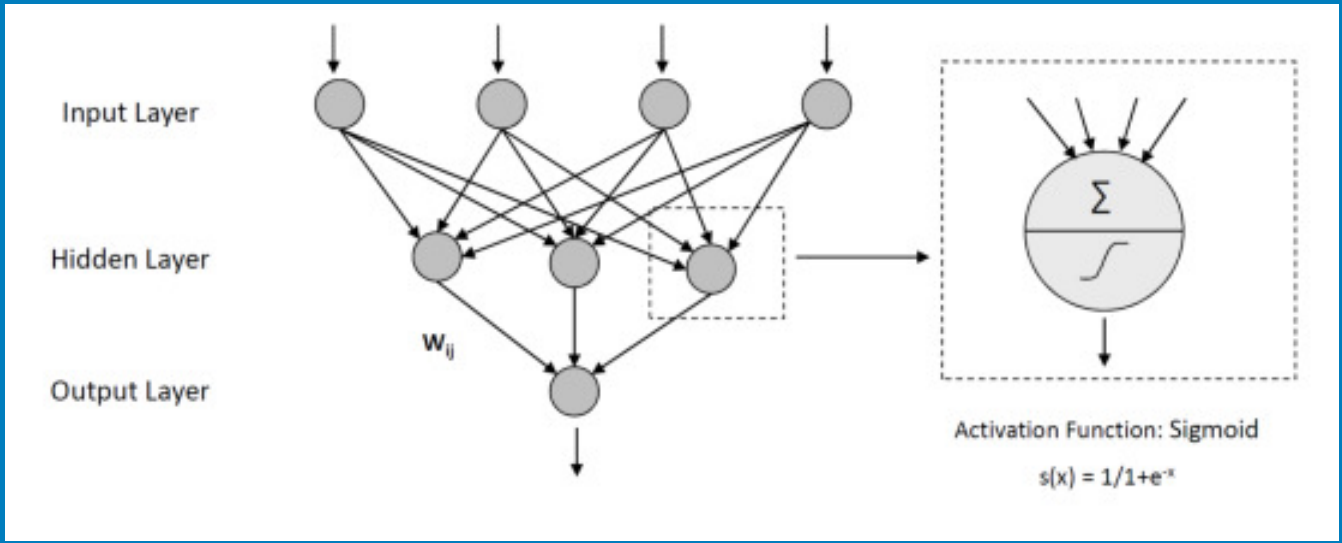
- **Connection between the neurons by weights w**
  - Enforce or reduce the level of the input information
  - Are directed, can be trained
- **Input signals**
  - Re-computed to a single input information: the propagation function
- **Output signals**
  - Activation function computes the output status of a neuron (often used: Sigmoid function)



Principle Setup of Artificial Neural Networks

Network Topology: MLP (Multi Layer Perceptron)

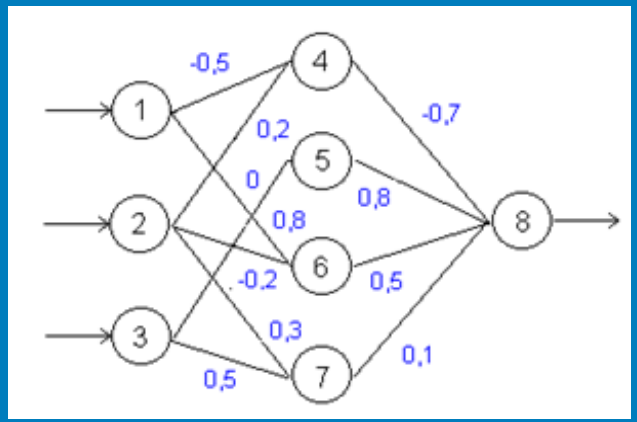
- Set-up of neurons in layers
- Direction and degree of connections
- Amount of hidden layers and neurons

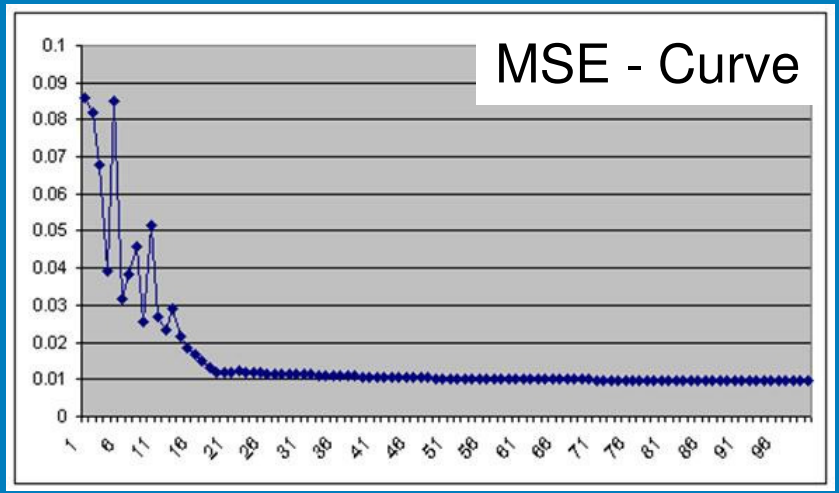


Training of Artificial Neural Networks

Learning Algorithm: Back-Propagation

- Repeated input of training data
- Modification of weights w
- Reduces error between expected and actual output of the network





Advantages / Disadvantages of Artificial Neural Networks

Advantages:

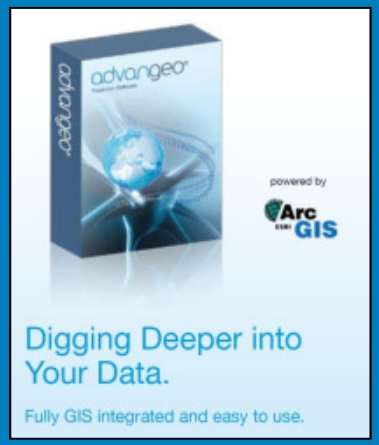
- ***learnable***: learning from examples
- ***generalization***: able to solve similar problems that have not been trained yet
- ***universal***: prediction, classification, pattern recognition
- able to analyze complex, non-linear relationships
- f***ault-tolerant*** against noisy data (e.g. face recognition)
- ***quickness***

Additional characteristics:

- choice of ***topology*** and ***training algorithm***
- ***black box system***: evaluation of weight of parameters

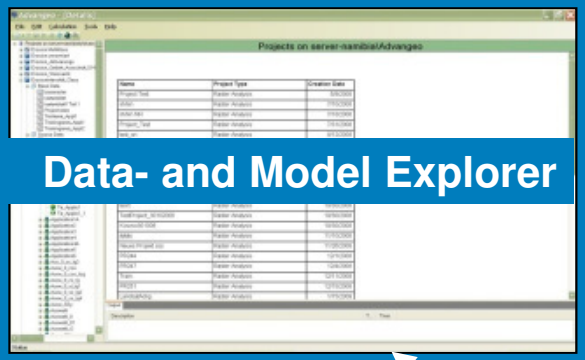
Software: advangeo

- Easy Access to Methods of Artificial Intelligence for Spatial Prediction
- Documentation of Working Steps
- Capture and Management of Metadata for Geodata
- Tools for Data Pre-Processing, Post-Processing and Cartographic Presentation
- Integration into Standard ESRI ArcGIS-Software



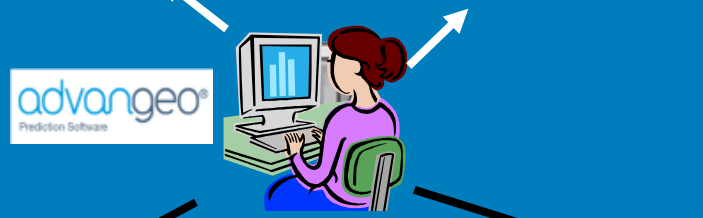
advangeo®
Prediction Software

Software Components



Data- and Model Explorer

GIS Extension



Referenced
Data Sources

Application
Metadata

Spatial
Data

advangeo: Work Flow / Methodology

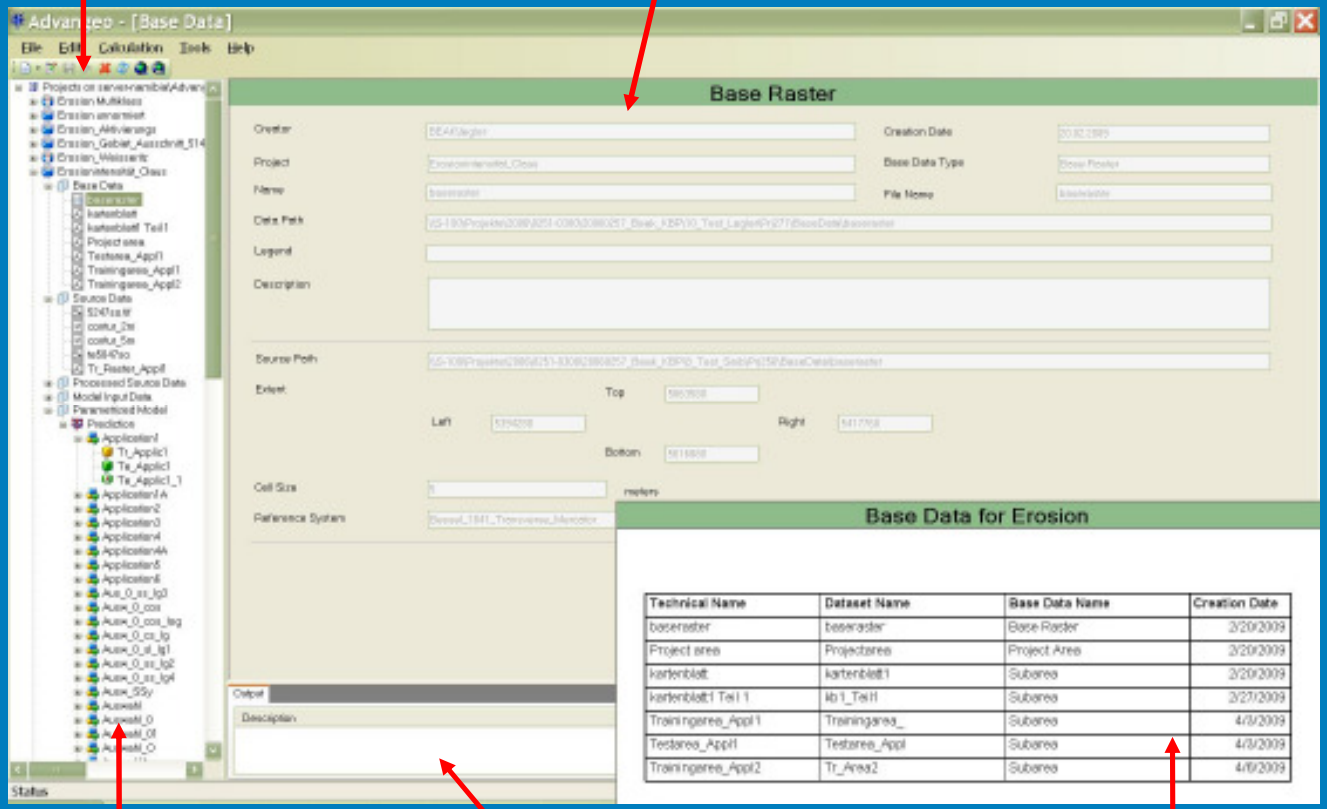
Working Steps:

1. **Task description**
2. **Definition of working area borders**
3. **Collection of primary source data**
4. **Processing of model input data**
5. **Statistical pre-processing**
   (unit transformation, data recoding, reduction of dimensions, …)
6. **Modeling of training and application scenarios**
7. **Statistical post-processing**
   (appraisal of repeatability, robustness, …)
8. **Presentation of prediction results**

advangeo: Data and Model Explorer

Menu & Toolbar
With Tools and Functionality

Form for Collection, Processing and Display of Data Objects and Models



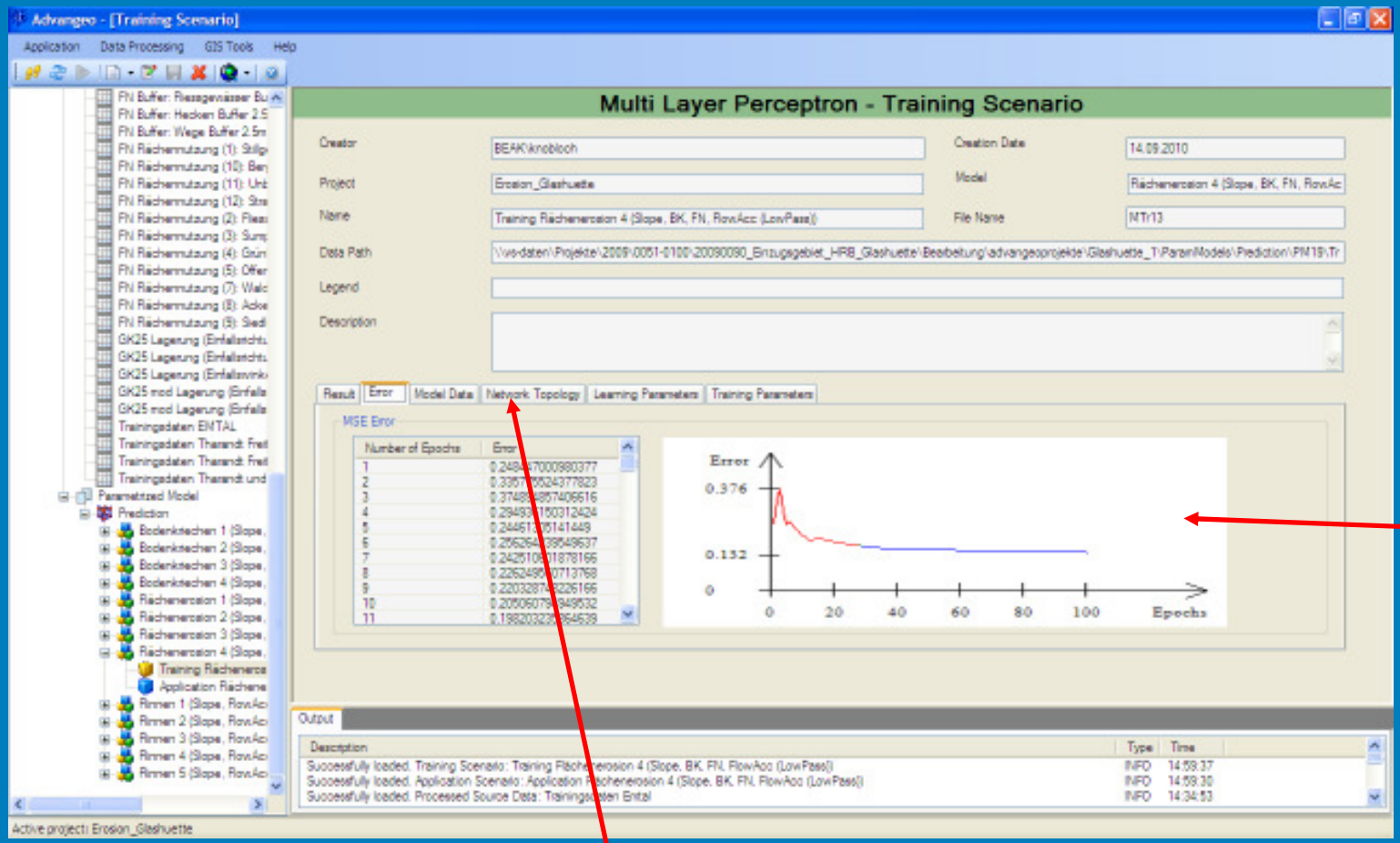
Technical Name	Dataset Name	Base Data Name	Creation Date
baseraster	baseraster	Base Raster	2/20/2009
Project area	Projectarea	Project Area	2/20/2009
kartenblatt	kartenblatt1	Subarea	2/20/2009
kartenblatt1 Teil 1	kb1_Teil1	Subarea	2/27/2009
Trainingarea_Appl1	Trainingarea_	Subarea	4/3/2009
Testarea_Appl1	Testarea_Appl	Subarea	4/3/2009
Trainingarea_Appl2	Tr_Area2	Subarea	4/9/2009

Explorer for Project Navigation with Context Functionality

Message Box with Information of Status, Warnings, Errors

Overview of Data Objects & Models

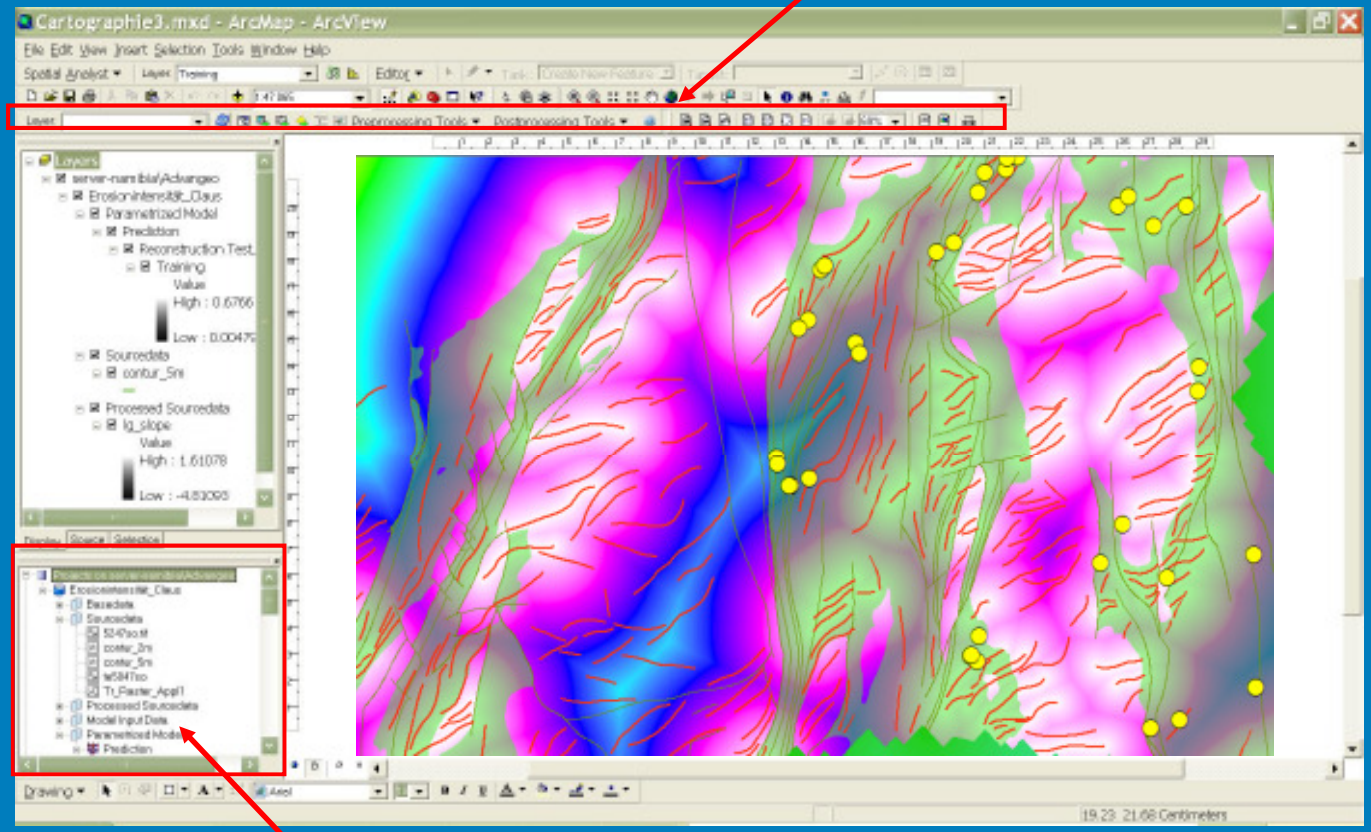
advangeo: Prediction Modeling



Selection of Model Input Data, Network Topology, Learning Parameter, Training Parameter

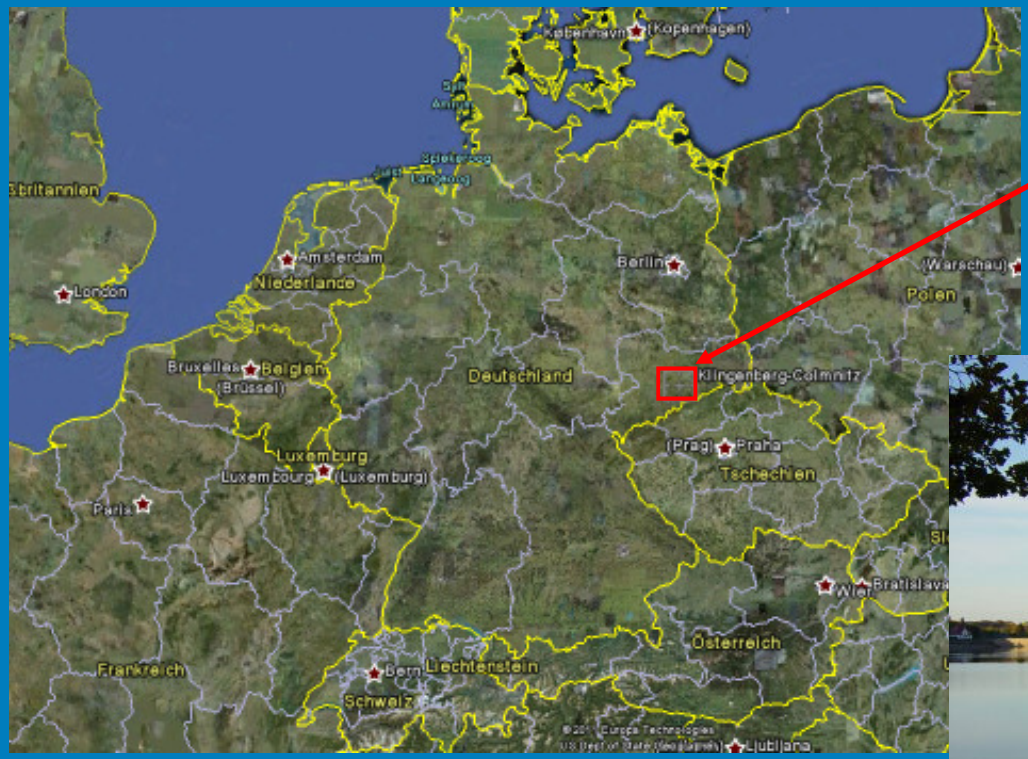
advangeo: GIS-Extension with Toolbar and Treeview

Toolbar with Tools for Data Processing and Communication with advangeo



Explorer with Project Data & Associated Context Menues for Quick Access to Project Layers and to Communicate witrh advangeo

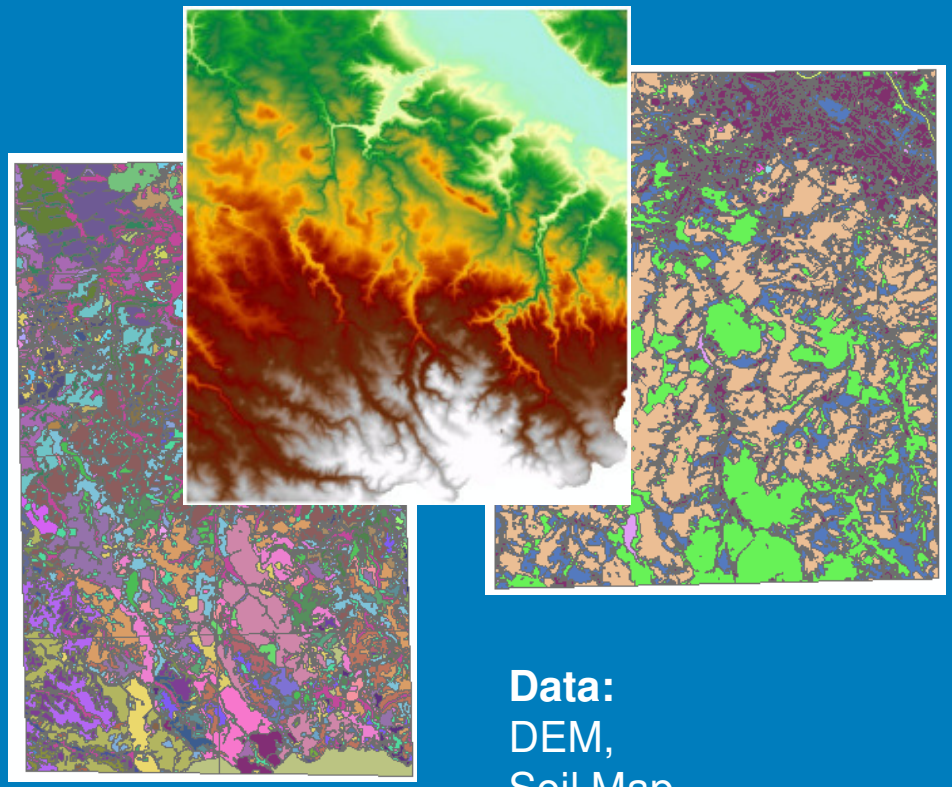
Case Study 1: Extensive Soil Erosion, Klingenberg (Germany)



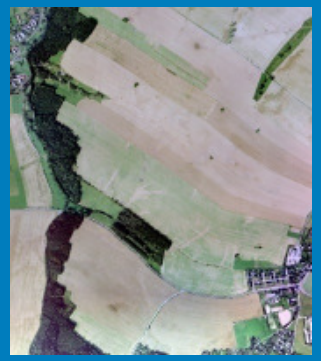
Klingenberg Reservoir Catchment Area

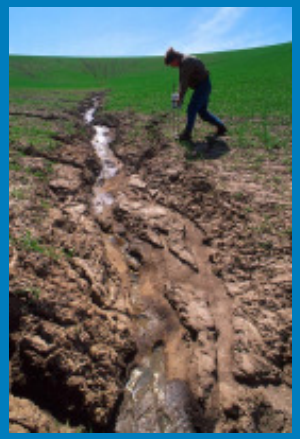
Case Study 1: Extensive Soil Erosion, Klingenberg (Germany)

Available Knowledge and Input Data

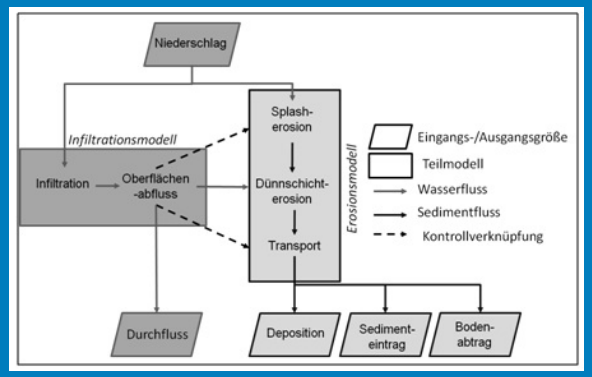


Data:
DEM,
Soil Map,
Landuse





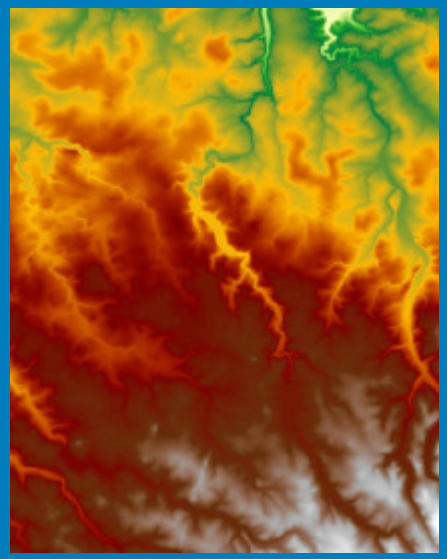
Knowledge: Aerial Images,
Field Observations



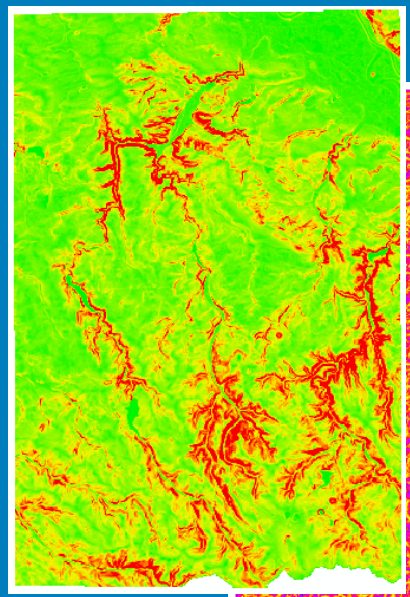
Knowledge: Analytical Models

Case Study 1: Extensive Soil Erosion, Klingenberg (Germany)

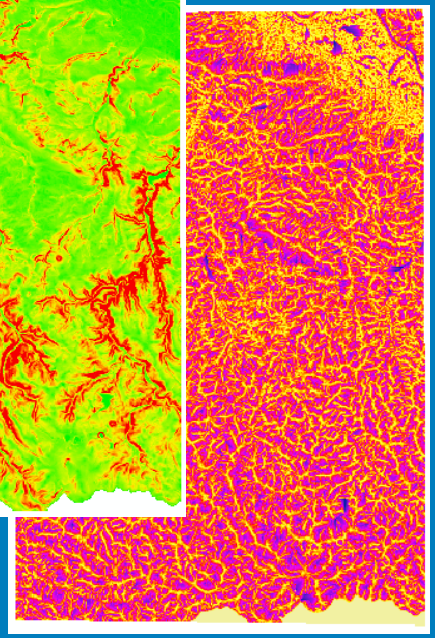
Input Data: Derivate of the Digital Elevation Model
→ Slope



DEM Saxony 5m RESAMPLED



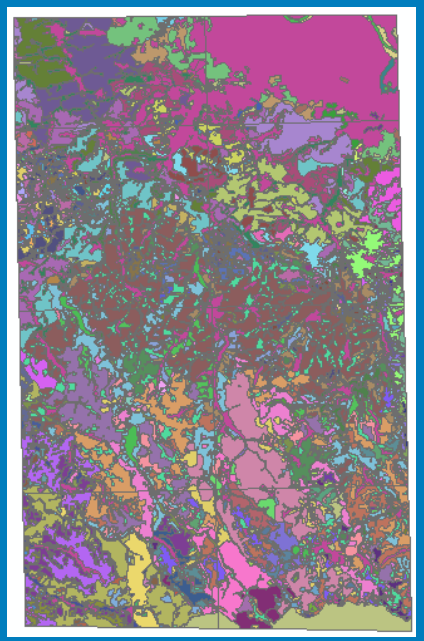
Slope [°]



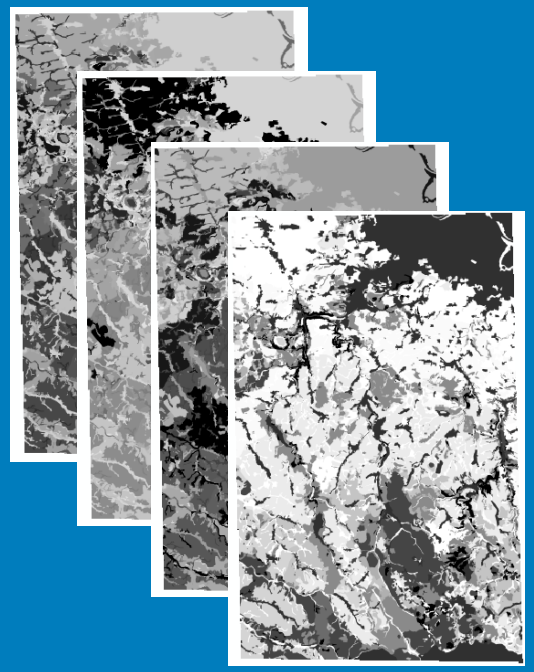
Log Flow Accumulation

Case Study 1: Extensive Soil Erosion, Klingenberg (Germany)

Input Data: Soil Map
→ Fine Soil (Clay, Silt, Sand), Skeleton Soil



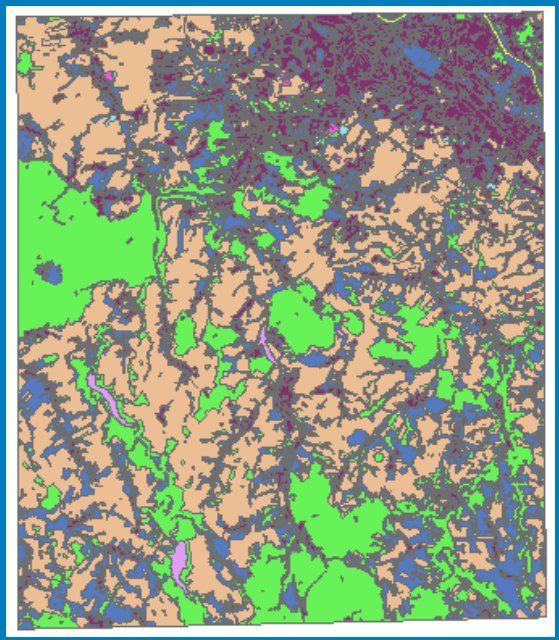
Soil Map



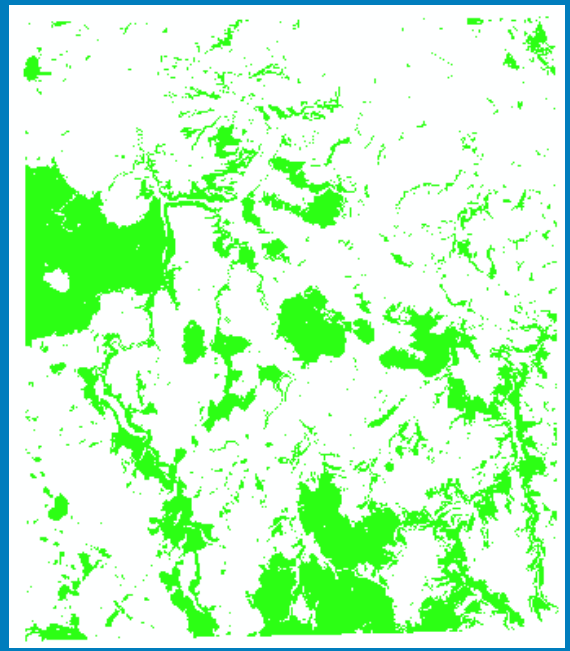
Fine Soil
(Clay, Silt, Sand), Skeleton Soil

Case Study 1: Extensive Soil Erosion, Klingenberg (Germany)

Input Data: Land use (ATKIS, Biotope Type Mapping)
→ Forest, arable land, pastures, wetland, etc.



Land use (ATKIS, Biotope Types)



Single raster for each land use class
(Forest, arable land, pastures, wetland., etc.)

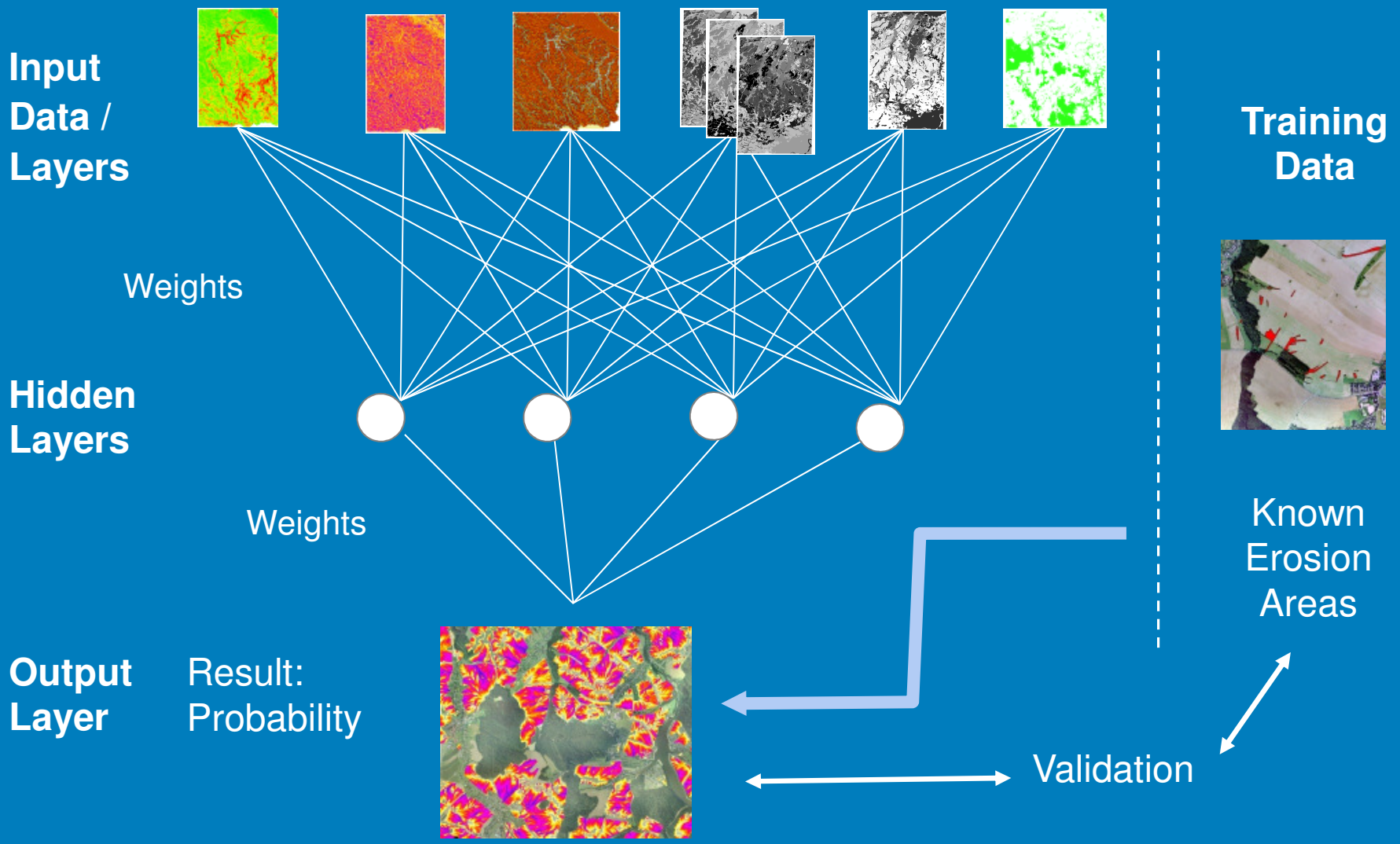
Case Study 1: Extensive Soil Erosion, Klingenberg (Germany)

Training Data: Based on Aerial Images
→ Mapping of Erosion Areas

Aerial Images – Intense Rainfall / Flood 2002

Mapped Erosion Areas

Case Study 1: Extensive Soil Erosion, Klingenberg (Germany)



Case Study 1: Extensive Soil Erosion, Klingenberg (Germany)

Input Data:

Slope

Silt, Clay, Sand

Probability:

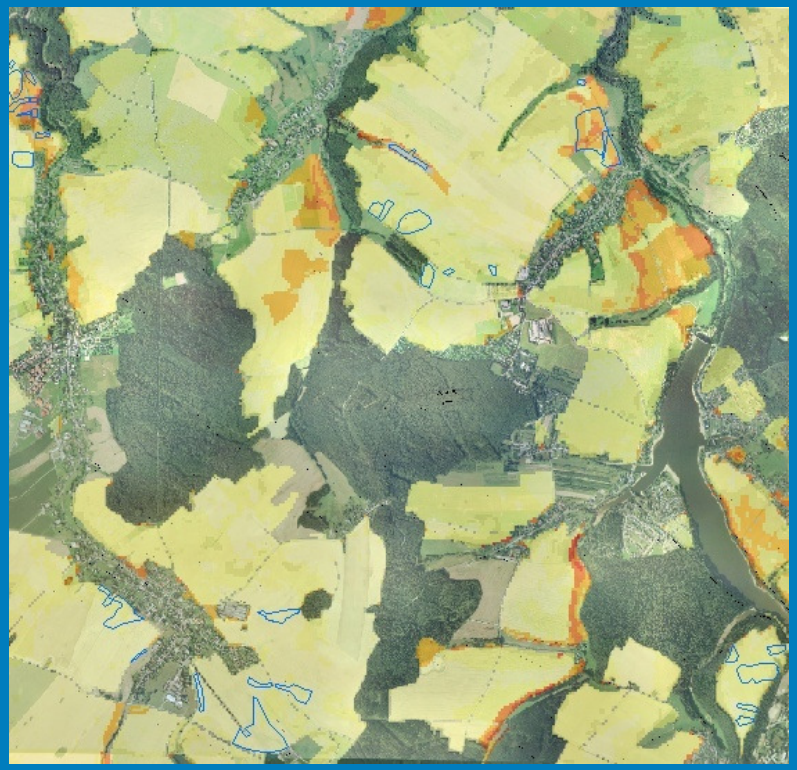
- 0.5 - 0.55
- 0.55 - 0.6
- 0.6 - 0.65
- 0.65 - 0.7
- 0.7 - 0.75
- 0.75 - 0.8
- 0.8 - 0.85
- 0.85 - 0.9
- 0.9 - 1

Case Study 1: Extensive Soil Erosion, Klingenberg (Germany)

Input Data:

Slope, Silt, Clay, Sand

+ Land use



Probability:

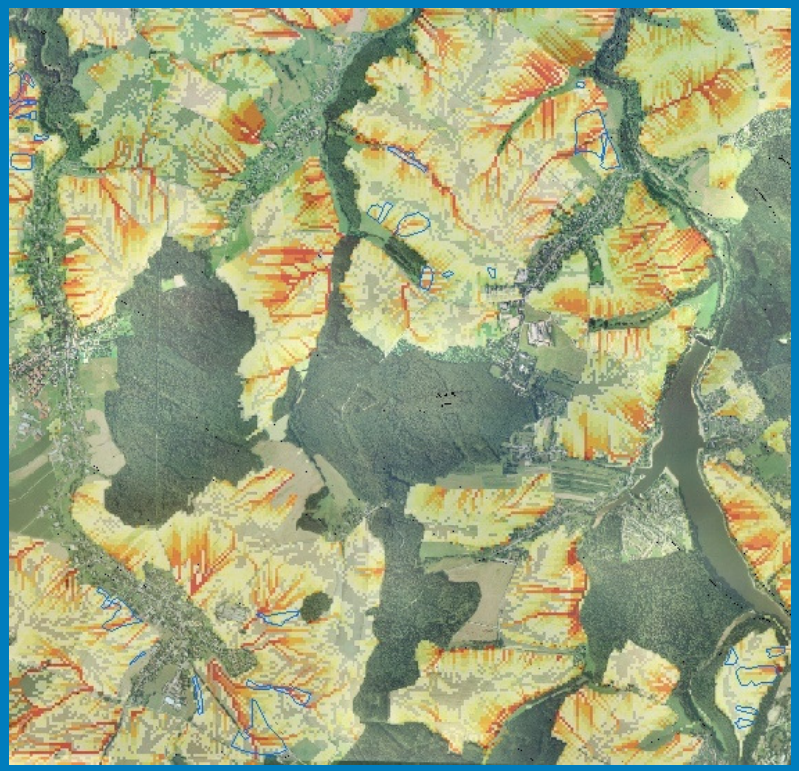
- 0.5 - 0.55
- 0.55 - 0.6
- 0.6 - 0.65
- 0.65 - 0.7
- 0.7 - 0.75
- 0.75 - 0.8
- 0.8 - 0.85
- 0.85 - 0.9
- 0.9 - 1

Case Study 1: Extensive Soil Erosion, Klingenberg (Germany)

Input Data:

Slope, Silt, Clay, Sand, Land use

+ Flow Accumulation



Probability:

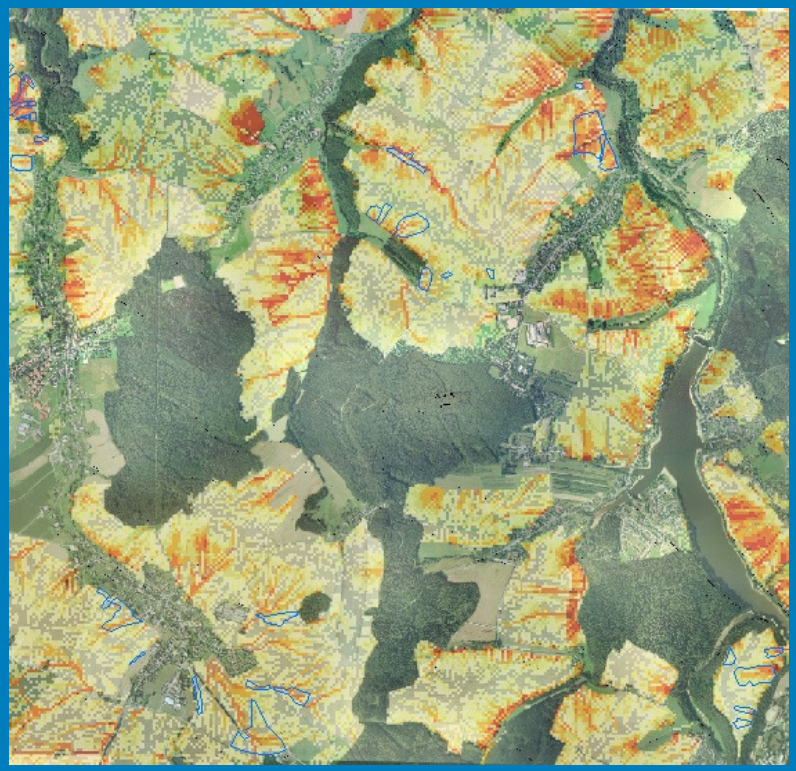
- 0.5 - 0.55
- 0.55 - 0.6
- 0.6 - 0.65
- 0.65 - 0.7
- 0.7 - 0.75
- 0.75 - 0.8
- 0.8 - 0.85
- 0.85 - 0.9
- 0.9 - 1

Case Study 1: Extensive Soil Erosion, Klingenberg (Germany)

Input Data:

Slope, Silt, Clay, Sand, Landuse, Flow Accumulation

+ Horizontal curvature



Re-Modeled Erosion Areas:

Training Areas

ca. 80 % of known erosion areas with p>75%

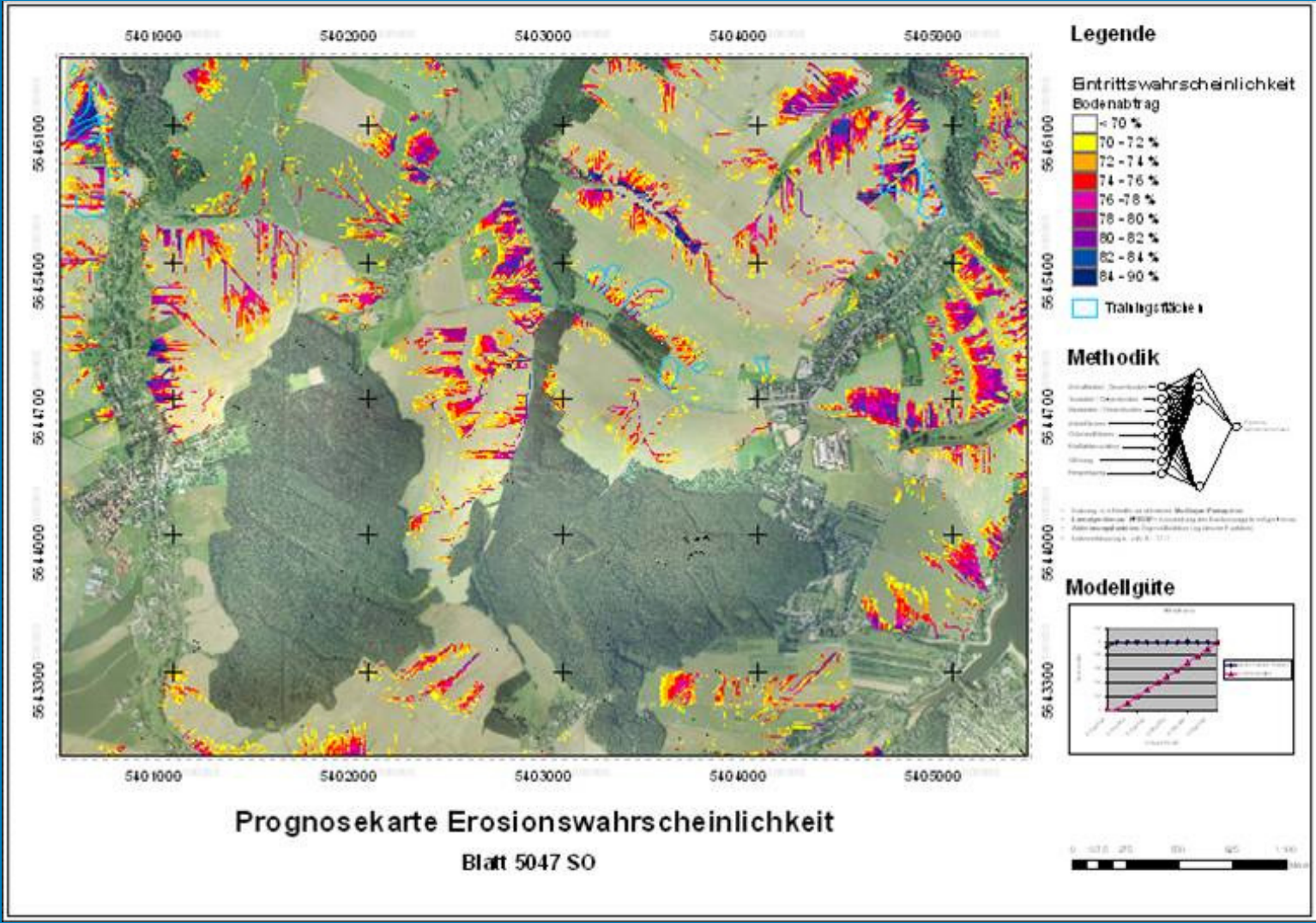
Test Area:

ca. 90 % of known erosion areas with p>75%

Probability:

- 0.5 - 0.55
- 0.55 - 0.6
- 0.6 - 0.65
- 0.65 - 0.7
- 0.7 - 0.75
- 0.75 - 0.8
- 0.8 - 0.85
- 0.85 - 0.9
- 0.9 - 1

Case Study 1: Extensive Soil Erosion, Klingenberg (Germany)

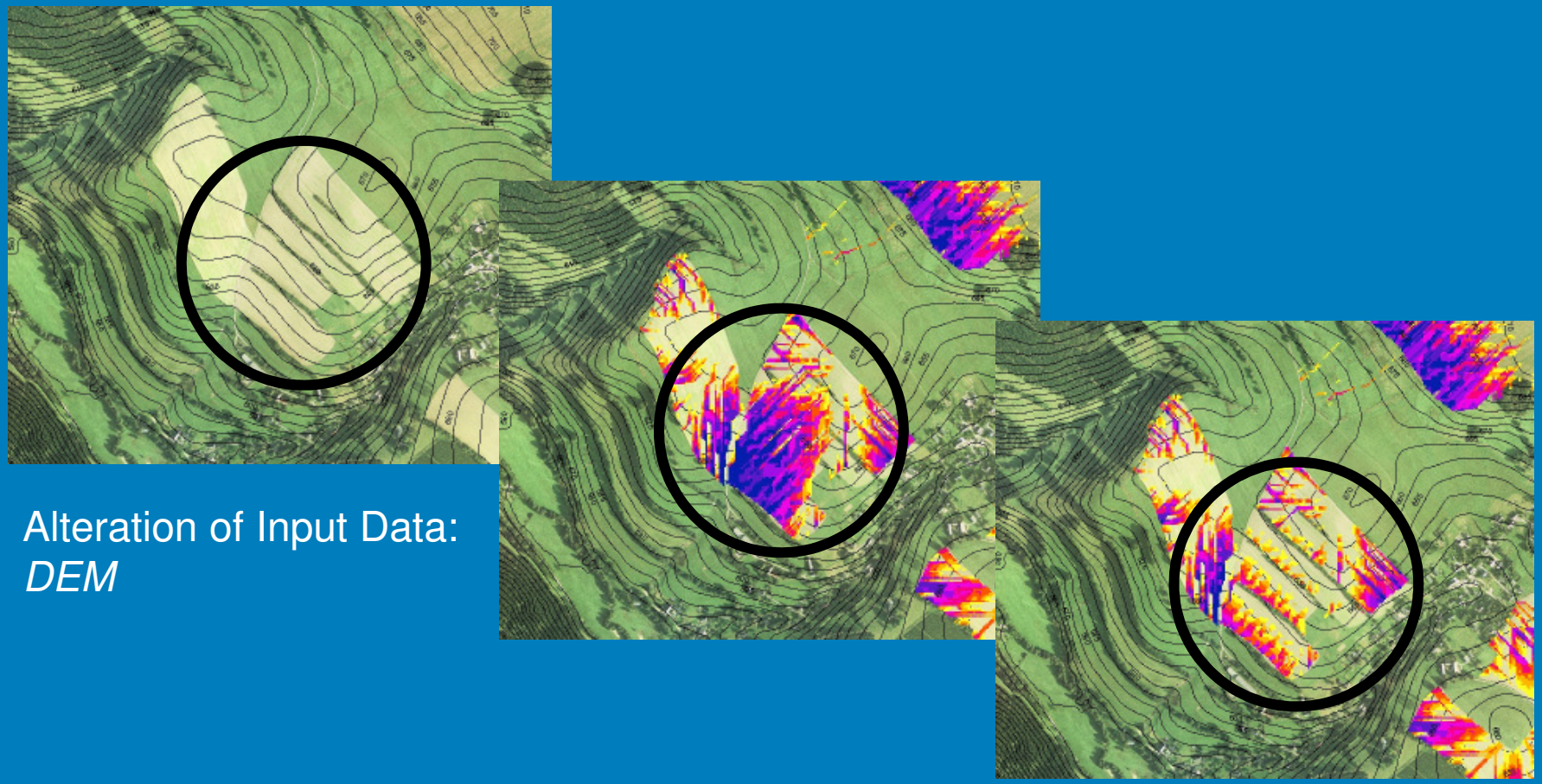


Case Study 1: Extensive Soil Erosion, Klingenberg (Germany)

Validation of Prediction Results in the Field

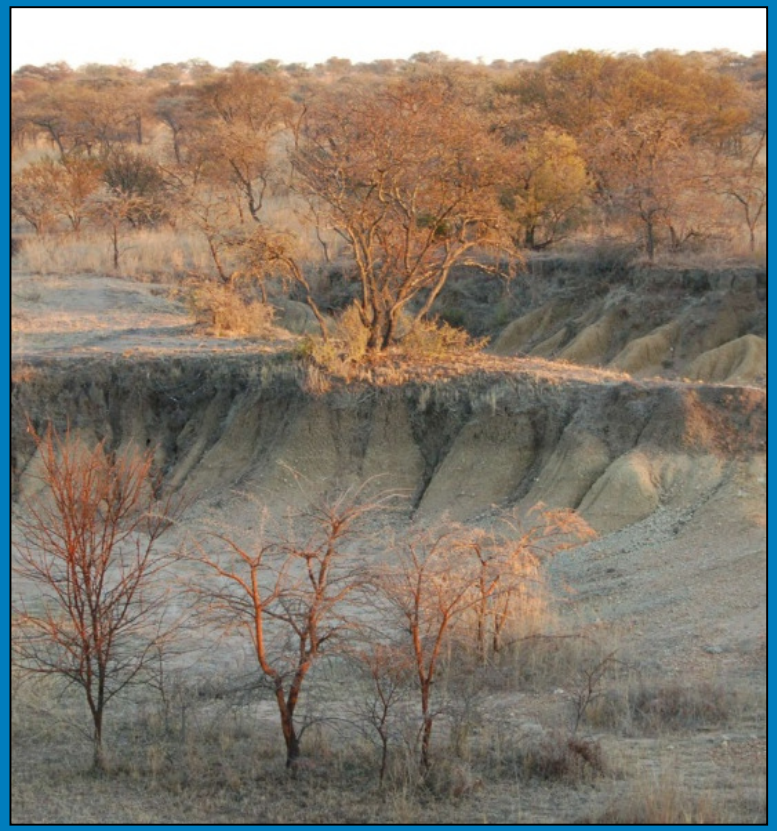
Case Study 1: Extensive Soil Erosion, Klingenberg (Germany)

Optimization of Protection Measures



Alteration of Input Data:
DEM

Case Study 2: Erosion Gullies, Limpopo (South Africa)



Council for Geoscience

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Case Study 2: Erosion Gullies, Limpopo (South Africa)

Republic of South Africa

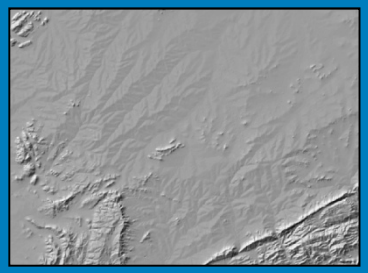
Limpopo Area

AEGOS

AFRICAN-EUROPEAN GEORESOURCES OBSERVATION SYSTEM

Case Study 2: Erosion Gullies, Limpopo (South Africa)

Input Data:
Elevation Model and its Derivates
Geological Map
Landuse



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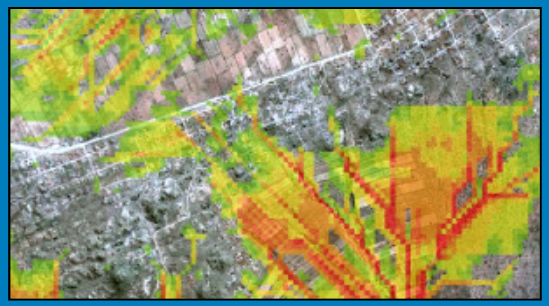
Trainings Data:
Observed Erosion Gullies from Aerial Images



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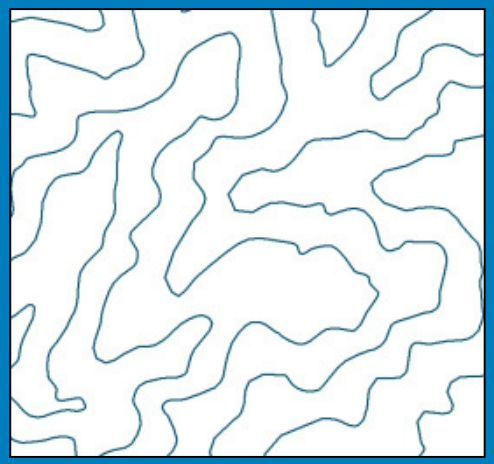
Available Data and Knowledge

- Digital terrain model (DTM)
  - Contour lines from Topographical maps: resolution depending on scale
  - ASTER GDEM: 30 m resolution
  - SRTM: 90 m resolution
- Derivates of the DTM
  - Slope,
  - Flow accumulation,
  - Flow length,
  - Slope contour (curvature)
- Landuse information
- Known erosion sites for training → taken from satellite images → Google Earth data

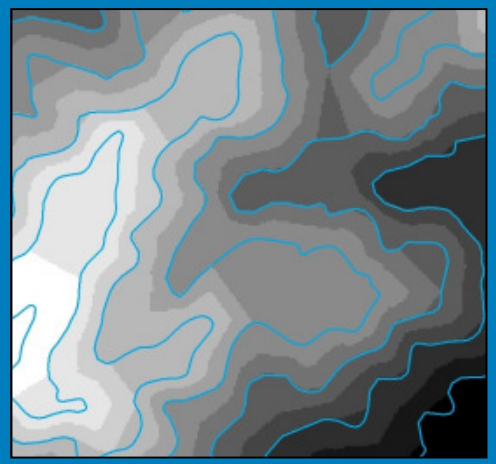
Case Study 2: Erosion Gullies, Limpopo (South Africa)

Input Data: *Contour Lines*

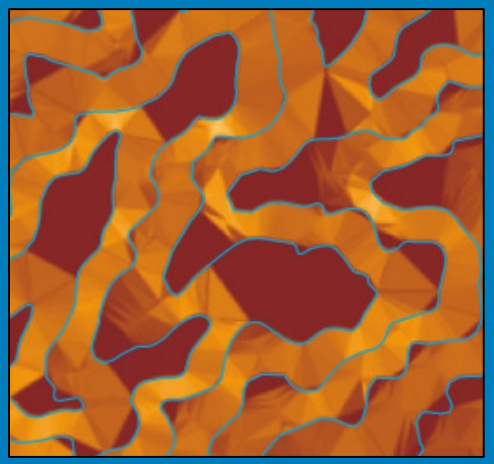
- Created by digitalization of topographic maps
- Conversion to elevation grid (method: triangulation)
  - Problem: generates areas of equal elevation and stair-like sections



20 m elevation contour lines



Elevation grid



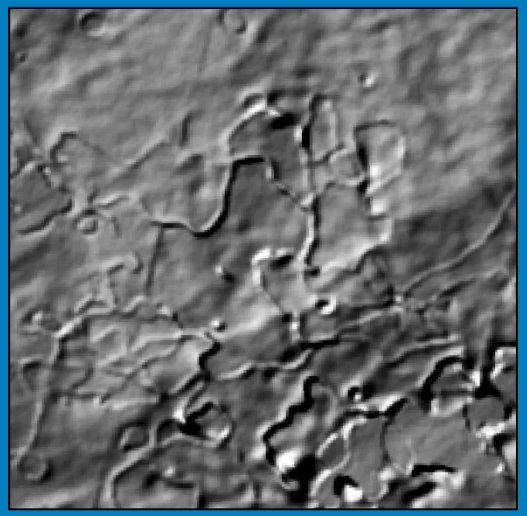
Slope grid

→ **The contour line generated DTM is not suitable for erosion modelling**

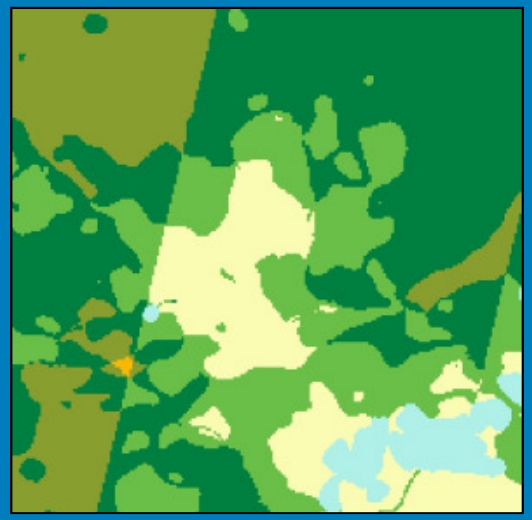
Case Study 2: Erosion Gullies, Limpopo (South Africa)

Input Data: *ASTER GDEM*

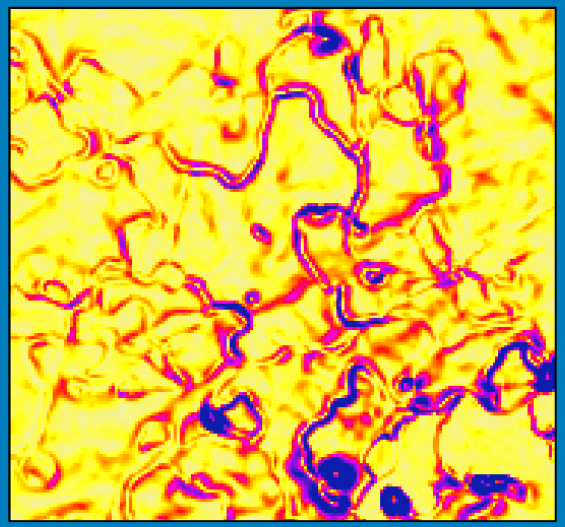
- Problem: variety of pervasive artifacts related to linear and curvilinear boundaries between different scene-based ASTER-DEMs (stack number)
- Artifacts appear as different geometric shapes and associate anomalous elevations (range from 1 m to more than 100 m)
- Usability can be reduced for certain applications (prediction of erosion) because of possible large elevation errors on local scale



ASTER GDEM hill-shade image



Boundaries of stack number areas (1 colour = 1 stack number)

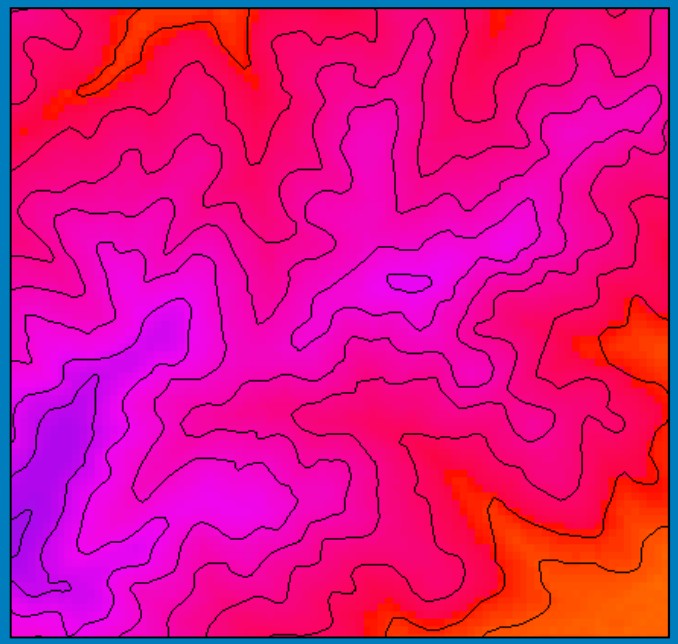


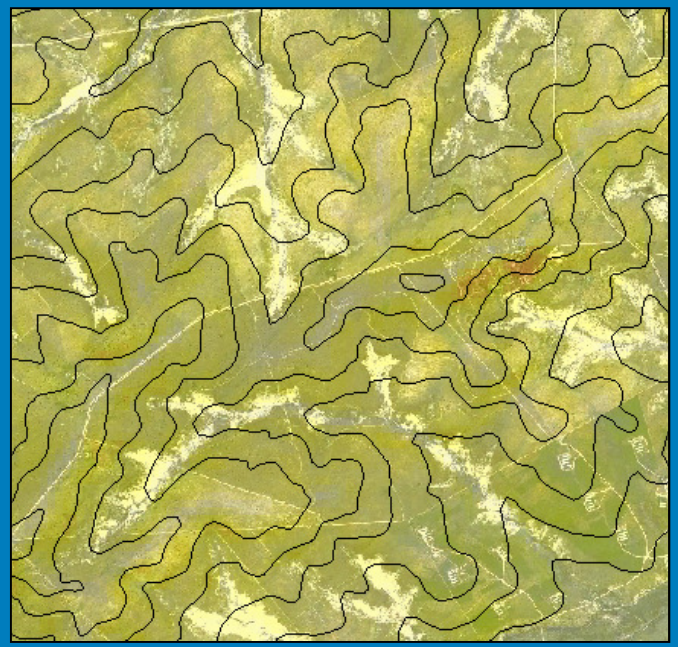
Slope angle

Case Study 2: Erosion Gullies, Limpopo (South Africa)

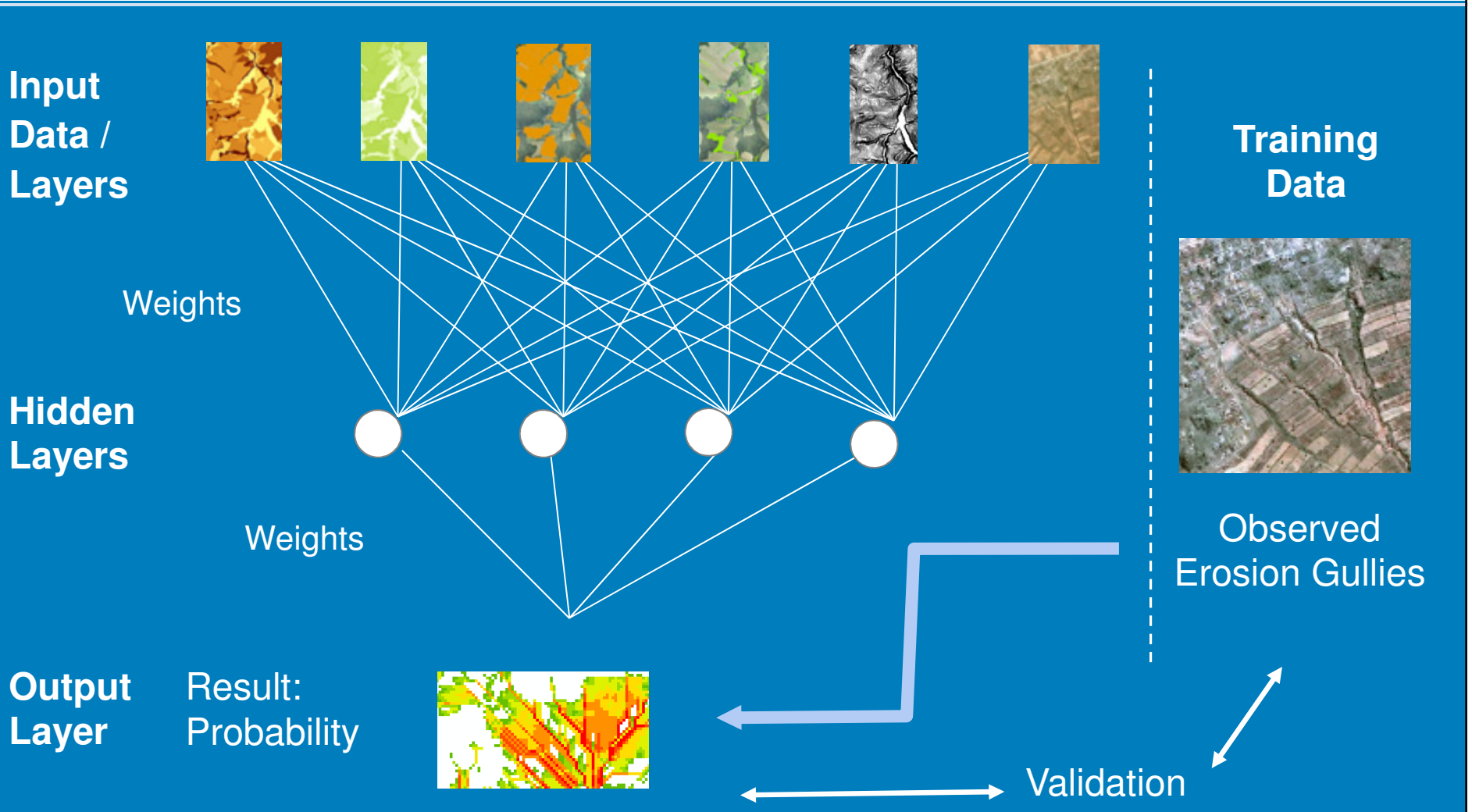
Input Data: *SRTM*

- Good fitting to the local elevation model
- No important inconsistencies have been observed so far
- Problem: Low resolution: 90 m → resolve it to 30 m

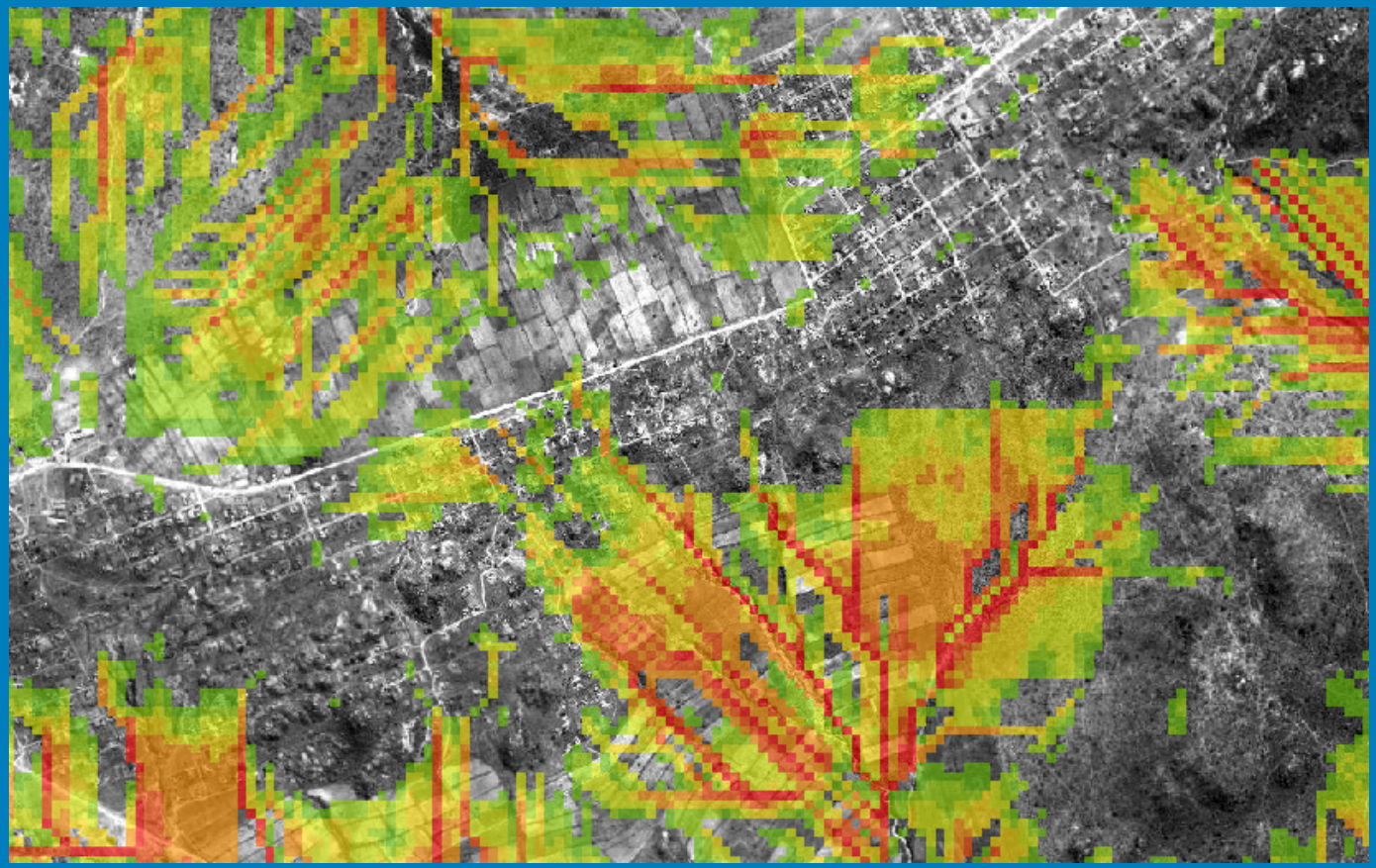




Case Study 2: Erosion Gullies, Limpopo (South Africa)



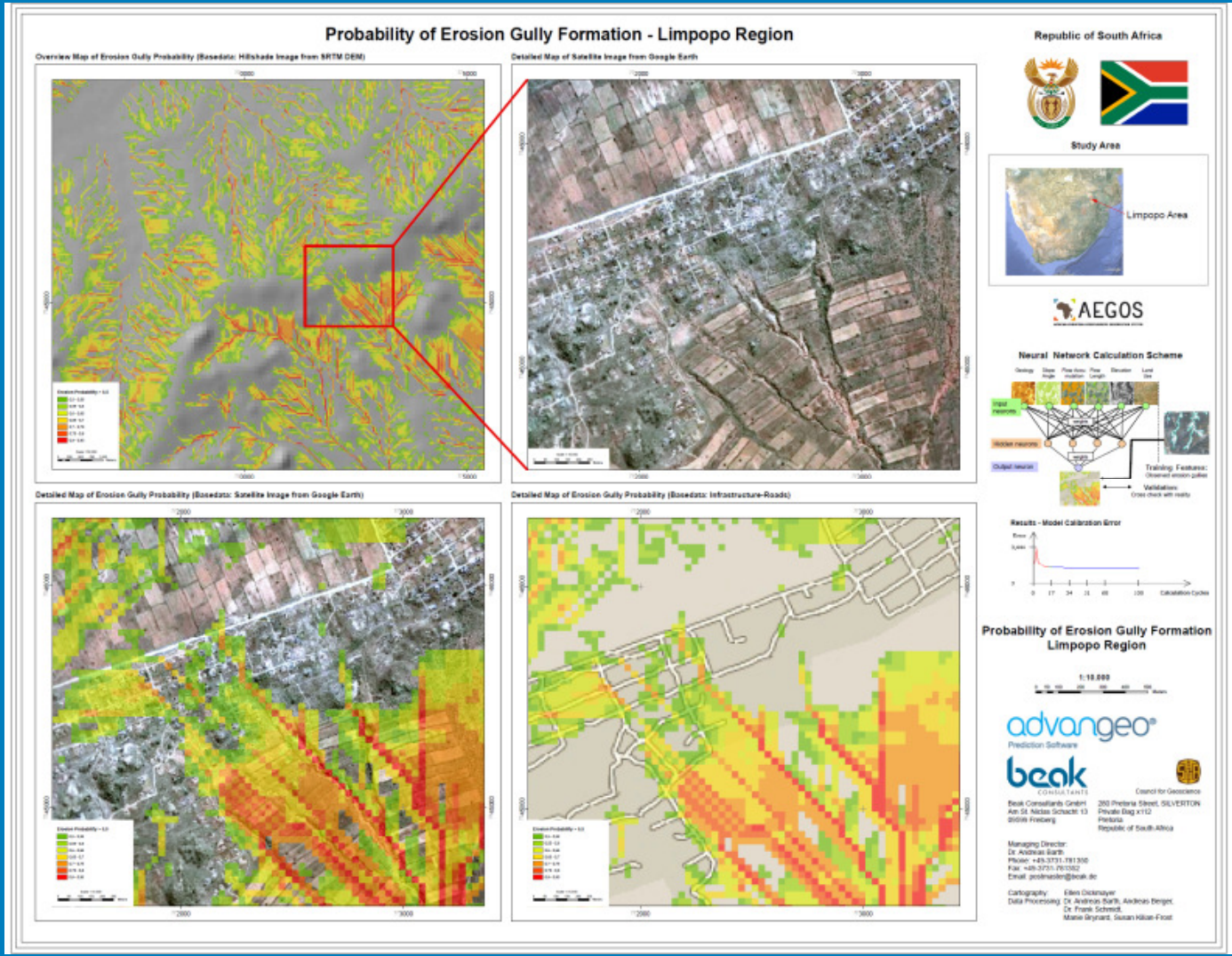
Case Study 2: Erosion Gullies, Limpopo (South Africa)



Erosion Probability > 0,5

- 0,5 - 0,55
- 0,55 - 0,6
- 0,6 - 0,65
- 0,65 - 0,7
- 0,7 - 0,75
- 0,75 - 0,8
- 0,8 - 0,93

Case Study 2: Erosion Gullies, Limpopo (South Africa)



Conclusion

- Erosion gullies can be predicted by using free data sources:
  - STRM elevation model data,
  - Information from Geological Maps,
  - Mapped training objects from Google Earth aerial images

- Complimentary data is required / desirable:
  - Detailed elevation model,
  - Land cover

- The target user groups are state and private bodies in:
  - Agriculture,
  - Urban planning (infrastructure),
  - Hazard prevention

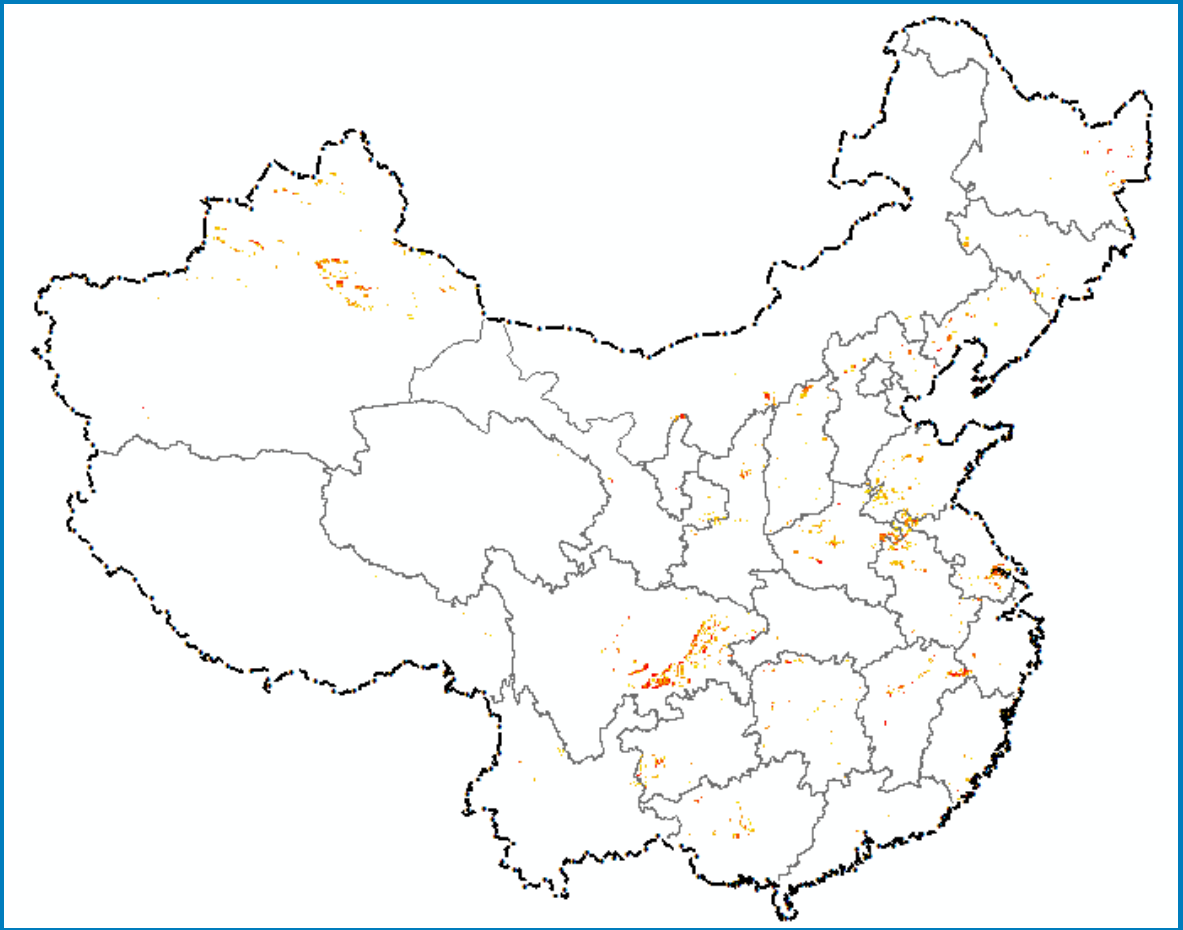
Further Case Studies

- **Soil Creeping, Formation of Erosion Gullies**: Freital / Germany (2009)
- **Extensive Soil Erosion, Soil Creeping, Formation of Erosion Gullies**: Glashütte / Germany (LTV Sachsen, 2010)
- **Coal Fires**: China (TUBAF, 2010)

- **Manganese Nodules Coverage Density**: Clarion-Clipperton Zone / Pacific Ocean (BGR, 2010)
- **Mineral Deposits / Occurrences - Pb/Zn, Au, Cr**: Kosovo (ICMM, 2003 – 2009)
- **Clay Mineral Classification**: Burkina Faso (Vaclav Metelka, 2010)
- **Soil Contaminations in Urban Areas**: Marienberg / Germany (LfULG, 2010)
- **Spread of Forest Pests**: Tharandter Wald / Germany (Sachsenforst, 2009)

Further Case Studies: Coal Fires (China)

Coal Fire Probability Map of China

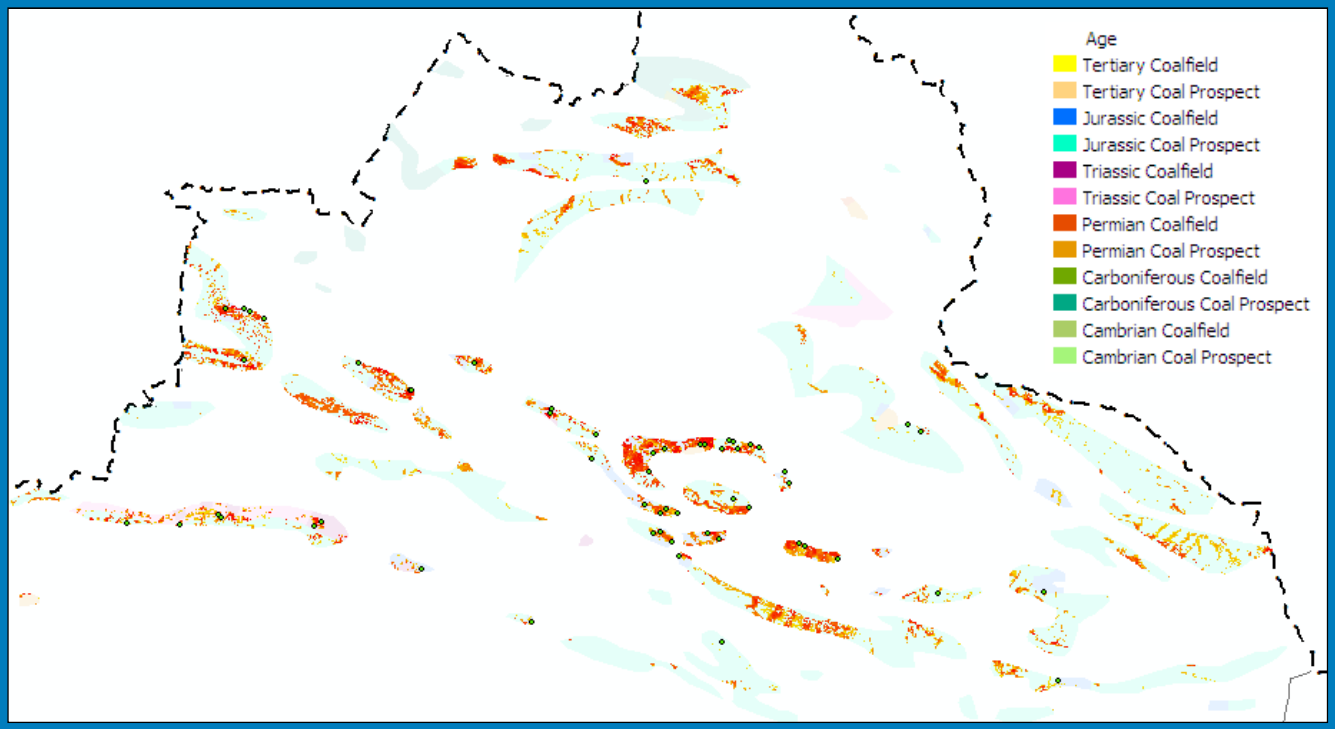


Coal Fire Probability

- 0 - 0,55
- 0,55 - 0,6
- 0,6 - 0,65
- 0,65 - 0,7
- 0,7 - 0,75
- 0,75 - 0,8
- 0,8 - 0,85
- 0,85 - 0,9
- 0,9 - 0,95
- 0,95 - 1

Further Case Studies: Coal Fires (China)

Detail Map: Northern Xinjiang Province



Coal Fire Probability

- 0 - 0,55
- 0,55 - 0,6
- 0,6 - 0,65
- 0,65 - 0,7
- 0,7 - 0,75
- 0,75 - 0,8
- 0,8 - 0,85
- 0,85 - 0,9
- 0,9 - 0,95
- 0,95 - 1

Summary: Application of Artificial Neural Netwroks

- Multiple applications of the developed methodology using artificial neural networks and GIS for the **prediction of geo-hazard**

- **Currently in development:**
  - Soil Parameter Regionalisation Model
  - Mineral Deposit Prediction Model

→ **We look forward to your questions, suggestions and comments and hope for future knowledge sharing and collaboration!**

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