A Tutorial Guide to using MI-SDM v2.50

based on
USGS Open-File Report 01-221
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Introduction

This tutorial is intended to guide you through the process of creating weights-of-evidence (**WofE**), fuzzy-logic (**FL**), and artificial neural network (**NN**) models using **MI-SDM**. We assume that you have a working knowledge of MapInfo Professional, and expect that you also have access to the MI-SDM User Guide (pdf or on-line help).

We will use the Carlin data set for modelling of Carlin gold deposits of central Nevada (western USA). These data are purposely selected to provide simple evidential layers for learning about the methods available in MI-SDM, and do not necessarily provide the best model of these deposits. This document summarizes the evidential layers and then discusses the processing steps required to create a WofE model. We also offer guidance for fuzzy-logic and artificial neural network analysis after completion of the WofE model. This document does not cover all data preparation or analysis functions and you should review the MI-SDM documentation for complete information on the options available.

We will discuss the WofE model in detail as it provides a foundation for many of the decisions necessary to complete a fuzzy-logic or artificial neural network model. Fuzzy membership values are often a useful approach to reclassification of categorical data in the artificial neural network model, as well as for controlling the number of classes that the artificial neural network has to deal with.

In this tutorial, the different analysis models are built using primarily geology and antimony evidence. For the WofE model, we also show the use of proximity to faults as evidence. The following additional evidential data layers are included in the data set for creating models that are more complex (and beyond the scope of this tutorial): multi-element stream sediment geochemistry, gravity, magnetics, and gamma ray (uranium, thorium, and potassium).

This tutorial has been adapted from the USGS open file report "Resource materials for a GIS spatial analysis course" by Gary L. Raines (USGS Open-File Report 01-221, Version 1.0, 2001), with some additional material included. The data source for this exercise has been translated into MapInfo format from Raines, Sawatzky, and Connors (1996) and is also available in its original format with the USGS open file report.

Summarized Metadata

Study area

Carlin StudyArea – polygon

The area to be studied and the analysis mask. All primary evidential layers have already been clipped to the extents of the study area. Evidential layers which will be derived from these primary layers (such as fault buffers, or classified geochemistry) will need to be clipped.

Training Points

Deposits – points

This layer defines the locations of known Carlin deposits in the study area. These locations are used by the supervised methods in MI-SDM to make a predictive model. The points are locations of deposits and occurrences that were classified by a group of experts as sediment hosted gold deposits (Carlin deposits).

Expert Assessment

Expert – classified grid

An example of a Carlin model made by experts using analogue methods.

This 3 class grid gives an example of a mineral assessment for Carlin deposits in the study area. It classifies the area into three categories, favourable, permissive, and non-permissive. The non-permissive category is assigned to areas where the probability of a deposit is so low that deposits are not expected to occur. Permissive areas are those where the age and lithology of the rocks are of the character associated with this deposit type. Favourable areas are those where processes associated with the formation of the deposit type are known to occur. This classified grid is derived from the USGS National Assessment (Ludington and Cox, 1996).

Evidential Layers

The following layers are provided to assist with prediction of Carlin deposit locations.

Geology

Geology – polygons

This polygon layer is extracted from 1:2,500,000-scale geology polygons from the King and Beikman map of the United States. The polygon layer contains attributes for lithological unit code, rock description and age order (1 is youngest and 134 is the oldest).

Geol_Codes – attribute table

This table describes some aspects of the geologic map units. Rockdesc contains the name of the geologic map units, and Carlin is a logical (T/F) field. T indicates that the unit is the same age or older than the Carlin deposits. F indicates that the unit is younger than the Carlin deposits. This is used to define which map units might be covering deposits.

Stream Sediment Geochemistry

StreamSed_naa – points

Point layer for antimony (and others) evidence. This is part of the NURE stream sediment geochemistry data. These data are normally considered 1:250,000 scale and the units are parts per million (ppm). The layer consists of a suite of element analyses by neutron activation. A value of zero (0) in this file indicates that the element was not analyzed in the particular sample. The antimony (naa_sb) measurements have been used to create Sb_ClassGrid using inverse distance weighting interpolation and system default parameters. Many additional layers for use in models could be created from this table.

Gridded Antimony

Sb_ClassGrid – grid file

The reclassification of antimony stream geochemistry (gridded with inverse distance interpolator and default parameters). The reclassification was done using ¼ standard deviation intervals, to give 15 values where 1 is the lowest and 16 the highest. The attribute table also contains 2 columns of fuzzy membership values.

Faults

Faults – polylines

This file contains faults shown on the 1:500,000-scale Geologic map of Nevada (Stewart and Carlson, 1978). This digital representation of the faults was created by digitization of the end points of straight-line sections of the faults. The attribute Nhem_az gives the northern-hemisphere azimuth of the faults. Faults with a northern-hemisphere azimuth near 330° can be buffered with 1000m-wide buffers to define areas proximal to Carlin deposits. Additional azimuthal groupings of faults might be used to define additional other layers.

Geophysics

Bouger – grid file

Bouger gravity anomaly at 20 milligal contour interval. This file is from Raines, Sawatzky, and Connors (1996). The source gravity data was widely spaced regional measurements.

Aeromag – grid file

Aeromagnetic data from the NURE program. The file is derived from Raines, Sawatzky, and Connors (1996). The source magnetic data were flown with 3-mile line spacing. The units are gammas.

Gamma Ray

Uranium – grid file

Uranium gamma-ray data from the NURE program. The file is derived from Raines, Sawatzky, and Connors (1996). The source gamma-ray data were flown with 3-mile line spacing. The units are equivalent uranium.

Thorium – grid file

Thorium gamma-ray data from the NURE program. The file is derived from Raines, Sawatzky, and Connors (1996). The source gamma-ray data were flown with 3-mile line spacing. The units are equivalent uranium.

Potassium – grid file

Potassium gamma-ray data from the NURE program. The file is derived from Raines, Sawatzky, and Connors (1996). The source gamma-ray data were flown with 3-mile line spacing. The units are equivalent uranium.

Overview of Data Preparation for MI-SDM

For this tutorial, many of the data sets have already been processed into a format suitable for direct input to MI-SDM. Because we will not look directly at many of the data preparation functions available in MI-SDM, an overview is presented here to assist you in preparing your own data. The table below shows some of the data preparation tasks that you can perform. Depending on the type of data, and what you are trying to achieve, some of these data preparation tasks may not be appropriate.

Input Data Type	Data Preparation Task	Use this Data Preparation Tool	Then use for
Any Data Type	Create a continuous grid of neighbourhood statistics	MI-SDM Neighbourhood Interpolation	Classify and analysis
Points, Polylines and Polygons	Interpolation feature density to a continuous grid surface	MI-SDM Density Interpolation	Classify and analysis
Points	Interpolate a variable to a continuous grid surface	MapInfo, Vertical Mapper, Discover, Geosoft, ER Mapper and (many) others	Fuzzy, Data Prep
Points	Create area-of-influence polygons	MapInfo Convex Hull or Voronoi MI-SDM Ring Buffer	Data Prep, WofE, NN
Points	Summary statistics and normalize	MI-SDM Statistics	Data Prep
Points	Aggregate point statistics to polygons	MI-SDM Points to Polygon Statistics	Data Prep, WofE, Fuzzy, NN
Points	Create drainage area polygons for stream sediment samples	StreamBuilder from Avantra Geosystems	Data Prep, WofE, NN
Lines, Polylines	Update attribute with bearing of line	MI-SDM Add Bearing	Ring Buffers, Density
Lines, Polylines	Buffer to polygons	MI-SDM Ring Buffer	WofE, Fuzzy, NN
Lines, Polylines	Extract points at intersections	MI-SDM Line Intersection	Ring Buffers, Density
Lines, Polylines	Identify bend and jog locations	MI-SDM Line Bends and Jogs	Data Prep
Lines, Polylines	Concatenate lines	MI-SDM Concatenate Lines	Data Prep
Polygons	Extract contacts	MI-SDM Extract Contacts	Ring Buffers, Density
Polygons	Classify and/or Generalize	MI-SDM Reclassify	WofE, Fuzzy, NN
Polygons	Rasterize to Classified or Continuous Grid	MI-SDM Polygons to Grid	WofE, Fuzzy, NN
Polygons	Update with grid statistics	MI-SDM Grid Statistics to Vector	WofE, Fuzzy, NN
Continuous Grids	Contour to solid polygons	Vertical Mapper and others	WofE, Fuzzy, NN

Input Data Type	Data Preparation Task	Use this Data Preparation Tool	Then use for
Continuous Grids	Transform and normalize	MI-SDM Transform	Fuzzy, Data Prep
Continuous Grids	Filter	MI-SDM Filter	Data Prep
Continuous Grids	Edge Detection	MI-SDM Edge Detection	Data Prep
Continuous Grids	Convert to Classified Grid	MI-SDM Classify a Continuous Grid MI-SDM Classify Grid by Histogram	WofE, Fuzzy, NN
Classified Grid	Reclassify	MI-SDM Reclassify	WofE, Fuzzy, NN
Classified Grid	Convert to polygons	MI-SDM Classified Grid to Polygons	WofE, Fuzzy, NN
Classified or Continuous Grids	Clip to selected polygons	MI-SDM Clip Grid to Polygon(s)	WofE, Fuzzy, NN
Classified or Continuous Grids	Perform maths operations on one or more grids	MI-SDM Grid Calculator	Data Prep, classify and analysis
Classified or Continuous Grids	Stitch multiple adjacent or overlapping grid tiles into one combined grid	MI-SDM Grid Stitch	WofE, Fuzzy, NN
Classified or Continuous Grids	Reproject classified or continuous grids from one coordinate system to another	MI-SDM Reproject a Grid	WofE, Fuzzy, NN

In the context of the Carlin data set that we are using for this tutorial, the following data preparation functions have been used (or in some cases will be used during this tutorial):

- Point data (stream sediment sample points) – create a continuous grid using interpolation, then classify to a set of discrete classes
- Polyline data (faults, folds) – create ring buffers
- Polygon data (geology) – convert to classified grid
- Continuous grids (geophysics) – transform to z-score
- Classified grids - reclassify

Set up MI-SDM and the Carlin Project

The first thing we need to do is to set up the MI-SDM project for Carlin data. The project definition lists the evidential layers and results tables associated with this project.

1. Run MI-SDM. When installed, MI-SDM is added to the list of tools shown in the Tool Manager (***Tools > Tool Manager***) and should be set to ***Autoload***. MI-SDM should be automatically loaded onto the main MapInfo menu bar, but if not then simply select MI-SDM from the Tool Manager and click the ***Loaded*** checkbox and ensure that the ***Autoload*** option is checked so that MI-SDM will be available on the main menu bar every time that MapInfo Professional is run.

2. Open the relevant datasets
   - Open all of the required evidential layers from the Carlin folder.
   - Make sure that the study area layer (StudyArea.tab) is in the front map window.

3. Define a new project in MI-SDM. Choose the ***MI-SDM > Set Project Parameters*** menu item and click the ***New Project*** button.
   - Enter a name for the project and a project directory. The project directory is where modelling and analysis results will be written. It does not need to be in the same location as the evidential layers (indeed they could be stored in a number of different locations).
   - Click ***Next*** and set the ***Study Area*** layer to StudyArea, and set the unit area to 1 km.
   - Click ***Next*** and set the ***Training Point*** layer to Deposits. We can choose to use a subset of training points, and we can also check if any training points do not lie within the study area. For the Carlin data, we will ***Use all points in table***.
   - Click ***Next*** and choose all of the evidential layers that will be used for this project. Each time that you choose this project in MI-SDM, these evidential layers will be opened if not already. You can modify this list (add or remove layers) by choosing ***Modify Project*** from the ***Set Project Parameters*** dialog.
   - Click ***Next*** and note the ***Class Column*** and ***Description*** column. Then click ***Finish***. MI-SDM will now create the project file and add it to the list of projects. Click ***OK*** to choose the newly created project and dismiss the project selection dialog.

Check the evidential layers from the ***Project Explorer*** menu item. This shows the evidential layers in the project (allowing you to easily open a map window for selected layers) and provides a simple way to access any of the results tables created for this project, or modify project settings.

Weights-of-Evidence Modelling

You should review the MI-SDM User Guide (pdf or on-line help) to fully understand the menus and functions. We assume that you are familiar with relevant MapInfo Professional functions.

Evidential Layers

There are three evidential data layers that we will use to construct the Weights of Evidence model. Any of the other evidential layers can, of course, be used in a similar method.

- **Geology** – This is a polygon layer which we want to convert to a classified grid, and then reclassify. Polygon layers can be used in weights of evidence modelling, but classified grids are processed much quicker.
    - There is a geology code look-up table (Geol_Codes) which will be used to define map units that are younger than the deposits and therefore potentially covering map units which contain deposits. We will use this table to define areas of missing data.
- **Faults** – This polyline layer contains faults and northern hemisphere azimuths so the faults can be selected by azimuth for proximity analysis.
- **Sb_ClassGrid** – this grid is a classification of a continuous grid of naa-sb into 16 integer classes based on standard deviations. There are three reclassifications of this grid for modelling (Pattern1, Pattern2 and Pattern3). FM1 and FM2 are examples of fuzzy membership values, which are discussed below in the section on fuzzy-logic modelling.

Analysis of the categorical evidential Layer

The geology layer, Geology_Grid, has 25 categorical classes – ie. the class values are not ordered and there is no numerical relationship between class values (class magnitude is in no way related to prospectivity, unlike the class values in a geochemistry or geophysics layer). In order to use this layer in Weights of Evidence, we want to convert to classified grid and then reclassify it into a binary map with areas associated with training points (inside the pattern) and areas not associated with training sites (outside the pattern, also referred to as off-pattern). Additionally, areas of missing data will be defined using the table Geol_Codes.

Convert Polygons to Classified Grid

Make sure that the project has been selected (in Set Project Parameters)

- Data Preparation Tools > Polygons to Grid
- Check the Geology layer name in the layer list and a screen is displayed with parameters for this layer.

- We will choose the Classified Grid in the ***Grid Type*** options
- Select Order for the class column and Unit for the description column
- If there were areas with no polygons, we would probably want them converted to null cells in the classified grid, however the geology layer completely covers the study area.
- Click ***OK*** to return to the first screen.
- In ***Grid Size Parameters***, choose the ***Convert area within study area*** option, and set the Grid Cell size to a value of 250m (which is suitable for this dataset).
- Click the Add to current project checkbox.
- Click *OK* and after processing, the classified grid is displayed in a mapper.

Note that the classified grid is displayed as a grid and can be recoloured using grid colouring functions (with both MapInfo and MI-SDM), but also has attributes. Use the ***Classified Grid Info*** tool to check the attributes for any location, and browse the attribute table (Geology_Grid_Att), which shows 1 record for each class as opposed to the original geology layer which contains 1 record for each polygon.

Calculate Layer Weights

Weights of Evidence > Calculate Layer Weights – use this function to explore the association of geological map units with the training points.

- Check Evidential Layer – Geology_Grid
- Select Class Column – Class
- Select Description Column – None
- Check Weights Calculation Options – Categorical
- Check ***Weights Output Options*** – Join to Evidential Layer. The results will be written into new columns in the Geology_Grid_att attribute table.
- After clicking ***OK***, inspect the contents of Geol_Grid_att.
    - Those map units with contrast greater than zero contain more points than expected by chance and are associated with the training points. Those units with contrast less than or equal to zero likewise contain fewer training points than would be expected by chance. The units that contain no training points lack a contrast value because contrast cannot be calculated.

Generalize the Geology Layer

Data Preparation Tools > Classify and Generalize Evidential Layer – we will use this function to reclassify (generalize) the geology layer into a binary layer based on the weights contrast information.

Generalization of evidential layers can be accomplished by a number of means. Here, we will just use the MI-SDM tools, but you may also use MapInfo's table maintenance and table update functions or simply enter values directly into the browser.

- In the Classify Layers dialog, select Geology_Grid as the ***Layer to Classify***.
- Choose the ***Classify ranged (numeic) values*** option. We will use SQL with this method to generalize based on the geology weights contrast.
- Choose ***New Classes into Column*** – <New Column> and enter ClassByWt
- Choose ***Add Class Descriptions into Column*** – <New Column> and enter ClassByWtDesc.
- Choose Class Definition ***by Individual query***, to allow SQL expressions to be entered to define the new classes.
- Click the ***Add new Class*** button and enter "Contrast <= 0" into the expression builder, and click ***OK*** to accept this expression. Then enter 1 for ***Class Number*** and "Outside" for ***Class Description***.
- The new class is then displayed in the list of defined classes, with the expression, class value, class description and number of records in this class. The number of records remaining to be reclassified is shown at the top of the dialog.
- We will now define the second class with an expression of "Contrast > 0", class value of 2 and class description of "Inside".
- The number of records remaining should now be 0, with 20 records in class 1 (Outside) and 5 records in class 2 (inside). So the reclassification for all of the records has been defined.
- If you make an entry mistake in any of the queries, double-click on that class definition to edit it, or right-click and choose Delete.
- Click the OK button to complete the reclassification. This will add the two new fields as specified above to Geology_Grid containing the binary classification.

Missing Data

Some of the geological units are younger than the training points so these map units should be reclassified to a distinct class, as they may have the potential to host deposits. We will flag these records in the geology layer from the Geol_Codes look-up table using standard MapInfo SQL functionality.

- Open the Geol_Codes table.
- From MapInfo's ***Table > Update*** menu option, add a new temporary column to Geology_Grid_Att for field Carlin from Geol_Codes, joining by lith code (for Geology_Grid) and Unit (for Geol_Codes).
- Select those records with ClassByWt = 1 and Carlin = "F".

- For the selected records, update ClassByWt = 3 and ClassByWtDesc = "Cover".
- With the geology layer now generalized from 25 classes to 3, you have the option of shading the geology grid by the new classes (using *Grid Analysis > Shade Classified Grid*), or even writing out a new classified grid containing just the new classes (and therefore discarding the original classes).

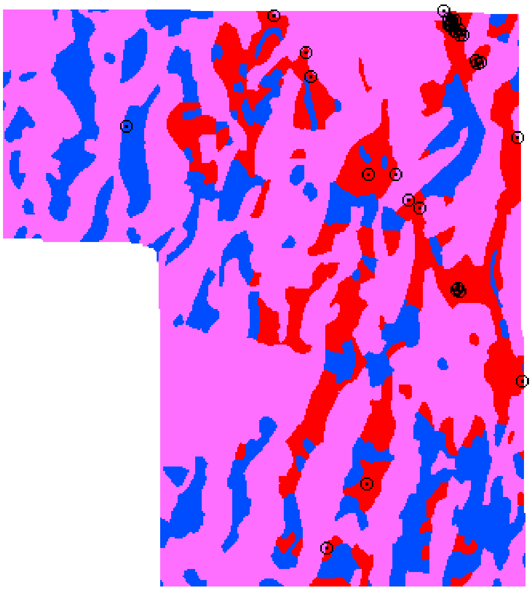


Figure 1 Generalized Geology layer with Training Points

Analyzing the Antimony Grids

The Antimony classified grid has been derived from stream sediment point samples, via a continuous grid. You may wish to re-create the continuous grid (for example use MapInfo's IDW interpolator and default settings), and then recreate the classified grid using MI-SDM's grid transform and grid classification functions.

We want to generalize the antimony stream sediment data into a binary evidential layer comprising areas associated with deposits (inside the pattern) and areas not associated with deposits (outside the pattern).

We will use the Sb_ClassGrid evidential layer that contains 16 ordered classes.

- *Weights of Evidence > Calculate Layer Weights* – explore the association of Sb_ClassGrid classes with the training points.
- Follow the same procedure as for the Geology layer except select Weights Calculation Options as *Cumulative Descending*. This will allow us to define a cut-off of the high values – ie. the values above which we will consider to be on the pattern (or inside).

- Inspect the layer weights to locate the maximum contrast – remember they are cumulative and not individual weights. For this layer, class 10 has the maximum contrast of 3.2

- To reclassify Sb_ClassGrid into binary classes, proceed with generalization as for the geology layer, except choose the *Classify categorical (unique) values* option. Then for Class Definition, choose *Multiple values per class* and *Build classes from values in column* Class.

- Click *Add new Class* and select classes 1-10 (>=1 to < 11), with a new class value 1 and description “Outside”.

- Add a second class for classes 11-16 with value 2 and description "Inside".

- Click *OK* to set the attribute values in column ClassByWt.

- As for the geology reclassification, you can choose to shade the grid by the new classes (using *Grid Analysis > Shade Classified Grid*).

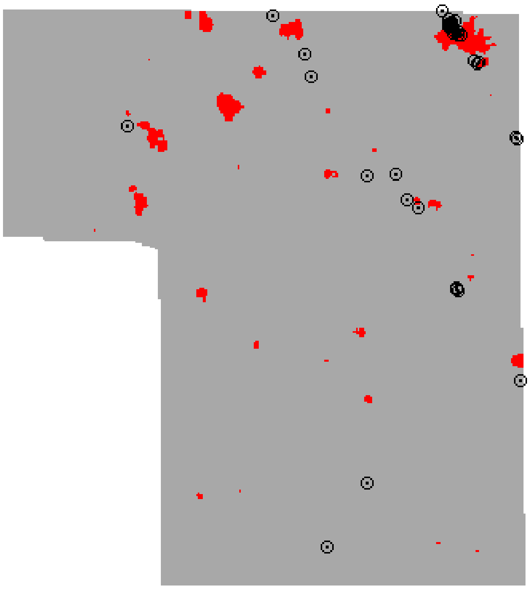


Figure 2 Generalized (binary) Antimony surface with Training Points

Adding the Faults layer to the Model

We can include many additional layers in our weights of evidence model. For the purposes of this exercise, we will look just at the faults layer.

- Using MapInfo’s *Table > Maintenance > Table Structure* menu item, add a new column called Octant (integer) to the fault layer.

- Using MI-SDM’s *Data Preparation Tools > Add Bearings to Lines* tool, populate the Octant column with octant values for line direction, so that a value of 8 will be 315-360, then use SQL Select to select all faults with Octant values of 4 and 8 (we need both NW and SE faults as we don’t know which direction the lines have been digitized in).

- Use *Data Preparation Tools > Ring Buffers* tool to create buffers around the selected faults. Create 5 ring buffers at 1000m increments.
- Convert the ring buffer polygons to a classified grid using the *Data Preparation Tools > Polygons to Grid* function. Check the Add to Project option, and set the grid cell size to a useful value (maybe 250m). Select the layer to convert, then we need to set the class column to the value in column Ring_, and set empty cells to a value such as 0. This will ensure that the entire area not covered by the ring buffers is given a class value of 0 rather than a null value. If the empty areas were left as null, then MI-SDM treats this as "missing data" for fuzzy logic and artificial neural network operations. This can give substantially different results as areas of missing data are assigned a value equal to the area-weighted average of all other classes.
- Use *Weights of Evidence > Calculate Layer Weights* function, selecting the Cumulative Ascending option, and then generalize the faults layer as before to produce a binary layer.

Combining the Evidential Layers

To integrate the evidential layers we will use the *Weights of Evidence > Create Unique Conditions Map* function. This produces the model shown in Figure 3.

- Choose the evidential layers to create the unique conditions map for.
- Choose the class column for each layer – these will default to the class column chosen when the layer was first added to this project. For the Geology and Sb layers, you should choose the column created during the generalization process above (we called this column ClassByWt).
- In the Unique Conditions dialog box, choose the *Calculate Weights and Variances* option. This will create a table listing the weights and variances for each input layer, as well as weights statistics for each unique condition.
- Check the *Calculate Conditional Independence* option. This will create a table of chi-squared values and associated probabilities for a pairwise test of conditional independence.
- After the unique conditions map has been generated, and weights written for each unique condition, an Overall Test of Conditional Independence will be displayed. If you used only the Geology and Sb grid generalized as provided, the CI ratio will be 0.24.
- The unique conditions map will then be displayed, shaded by Posterior Probability.

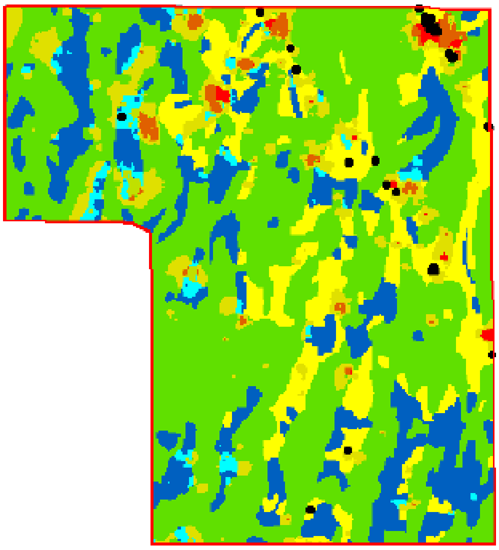


Figure 3 Posterior Probability map with Training points

The training points are shown as black dots. The highest to lowest probability values are shaded red, yellow, green, cyan, through blue.

Guidance for a Fuzzy-Logic Model

The primary decisions when making a fuzzy-logic model are to assign fuzzy memberships to the attributes of the model and to decide which fuzzy operators to apply. MI-SDM provides a tool to assist with assigning of fuzzy membership values to evidential data classes. MI-SDM also provides a ***fuzzification*** tool, which has the advantage that the fuzzy membership values are objectively and exactly reproducible and the process is easily reported.

For gaining experience in selection of fuzzy membership values, the contrast values from the WofE analysis, discussed above, provide useful guidance. For example, a contrast of zero is logically a fuzzy membership value of 0.5 (as it indicates no positive or negative spatial association with training points). Positive and negative contrast can be rescaled between 0 and 1. For those categorical classes that contain no training points and thus cannot have a contrast value, it is necessary to define a membership value. These categories might be assigned a membership value of zero or 0.5 if the category is a younger map unit that might cover a deposit that is a missing value in the WofE analysis.

Fuzzy membership values entered manually (using the ***Define Fuzzy Membership*** menu item) are included with the geology and reclassified antimony grids. These fuzzy membership values can be used with a fuzzy Gamma ($\gamma = 0.9$) to create the model shown in Figure 4. This fuzzy model is by design similar to the WofE posterior probability (Figure 3). Alternatively, the application of the fuzzification option is described below.

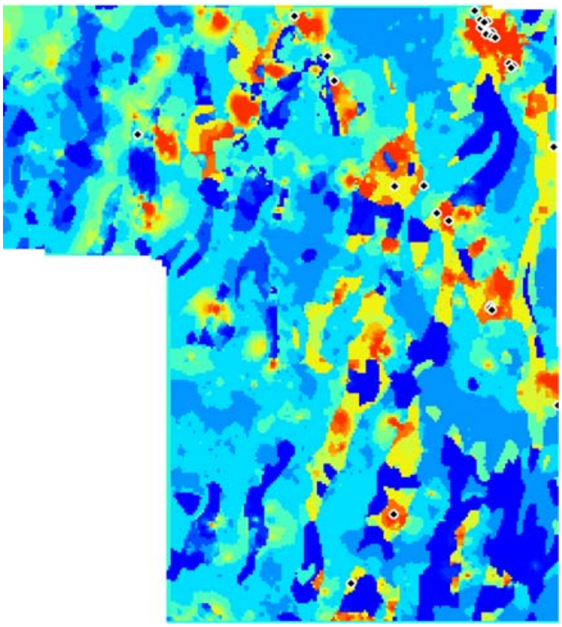


Figure 4 Fuzzy Or model using geology and antimony

The fuzzy membership values are FM1 for geology and antimony derived using the MI-SDM manual definition of fuzzy membership. The training points used for the WofE model are shown as black dots. The highest to lowest values are shaded from red through green to blue.

Fuzzification of Geology Evidence

We will use the process of fuzzification to generate fuzzy membership values for our evidential layers without requiring subjective input. For an introduction to the fuzzification process and the algorithms used, refer to the MI-SDM User Guide.

The intent is to calculate fuzzy membership values that reflect how the experts value the geological map units, but performed in a transparent and repeatable process.

We want to use Contrast values created for the geology layer, as described above (see section on Calculate Layer Weights). These contrast values need to be transformed to fit into the range [0,1] that is required for fuzzy logic operators.

In order to use the Large fuzzification function on contrast values, we need to deal with those classes for which contrast cannot be calculated – that is, those classes that contain no training points. These classes currently have a contrast value of 0, but this is really a null value. With reference to the reclassification by weights (see sections on Generalize the Geology Layer and Missing Data):

- Add column Contrast2 to Geology_Grid to hold the modified Contrast values, and update this new column with values from the Contrast column.
- First we will select all classes with NumPoints=0, and for this selection update Contrast2 to a value which is the same as the minimum value in Contrast (-3.2). These null values are most of the classes that were reclassified as Outside and Missing in the weights-of-evidence analysis.
- Now select those records where ClassByWtDesc = "Missing". As we have no information on the prospectivity of these classes, we want them to have fuzzy membership values of 0.5 so we must set their Contrast2 to 0.
- The values in Contrast2 will allow us to use a contrast of 0 as the mid value in the fuzzification process, which will give a fuzzy membership value of 0.5. The value of 0.5 is halfway in the range of fuzzy values between completely unprospective (0) and completely prospective (1).
- Run fuzzification with MI-SDM's ***Fuzzy Logic > Define Fuzzy Membership*** function and choose the Geology_Grid layer. Then set the Class Column to Contrast2 and click the ***Set values by Fuzzification*** button.
- Choose the Large function with no hedge and with a spread of 4 and mid of 0. The graph reflects these values as you enters them, so you can change the parameters to get the most suitable.
- Set the ***Minimum fuzzy value*** to 0.01, to ensure that the minimum contrast value gets a fuzzy membership value slightly greater than zero.
- Click OK to return to the Define Fuzzy Membership dialog and see the calculated values. If you are satisfied with these values, set the ***Save values to*** Geology_Grid_Att option, the ***Column*** to store fuzzy membership values to FM2 and click ***OK***. The fuzzy membership values will now be written to the attribute table.

Table 1 Attribute table for Geology_Grid showing fuzzification based on contrast.

The contrast values must first be adjusted so that null contrasts (those classes that have zero training points) are assigned some rescaled value. Fuzzification parameters for attribute FM are the following: function = Large, spread = 3, and mid = 0. This table is sorted on FM2 and ClassByWtDesc.

Attributes of Geology_Grid joined with Geology_Grid_Weights

Class	Code	ClassByWt	ClassByWtDesc	FM2	NumPoints	Contrast
7	TRPE	1	Outside	0.01	0	0
10	LTV	1	Outside	0.01	0	0
12	UPZ	1	Outside	0.01	0	0
13	KG	1	Outside	0.01	0	0
15	P	1	Outside	0.01	0	0
16	JG	1	Outside	0.01	0	0
18	TI	1	Outside	0.01	0	0
19	LMZV	1	Outside	0.01	0	0
21	TRG	1	Outside	0.01	0	0
22	KC	1	Outside	0.01	0	0
23	JMI	1	Outside	0.01	0	0
24	KG2	1	Outside	0.01	0	0
9	LMZ	1	Outside	0.257	1	-0.8
1	Q	-99	Missing	0.5	1	-3.2
3	TPC	-99	Missing	0.5	1	-0.2
2	TPF	-99	Missing	0.5	0	0
6	TMV	-99	Missing	0.5	0	0
8	TPV	-99	Missing	0.5	0	0
20	TMF	-99	Missing	0.5	0	0
25	QV	-99	Missing	0.5	0	0
14	UPZE	2	Inside	0.547	1	0.1
4	C	2	Inside	0.799	2	1.3
11	LPZ	2	Inside	0.859	6	1.8
17	UPZC	2	Inside	0.892	2	2.2
5	LPZE	2	Inside	0.923	20	2.8

Fuzzification of Antimony Evidence

The objective is to calculate fuzzy membership values for antimony by fuzzification similar to those manually defined in FM1, assuming these represent the opinion of the experts.

- Using the antimony evidence, Sb_ClassGrid, run fuzzification with the Large function, no hedge, and a mid value of 9.0. The minimum fuzzy membership value is set to 0.01.
- Select the Class column for the fuzzification. The Class column is the reclassification of the antimony by quarter standard deviation classes, with a value of 3 at the mean and 16 is more than 3 standard deviations above the mean.
- FM2, FM3, FM4, and FM5 are fuzzification for spreads of 3, 6, 12, and 24, respectively.

Table 2 Fuzzification of antimony evidence.

FM1 is an example of fuzzy membership values defined manually. FM2, FM3, FM4, and FM5 show examples of different fuzzification

Attributes Of Sb_ClassGrid

Class	Pattern3	Pattern3	FM1	FM2	FM3	FM4	FM5
1	1	Outside	0.06	0.010	0.010	0.010	0.010
2	1	Outside	0.08	0.012	0.010	0.010	0.010
4	1	Outside	0.12	0.060	0.013	0.010	0.010
5	1	Outside	0.13	0.120	0.025	0.010	0.010
6	1	Outside	0.16	0.204	0.066	0.014	0.010
7	1	Outside	0.17	0.304	0.160	0.040	0.011
8	1	Outside	0.19	0.407	0.317	0.176	0.049
9	1	Outside	0.21	0.505	0.505	0.505	0.505
10	2	Inside	0.81	0.592	0.673	0.806	0.945
11	2	Inside	0.84	0.665	0.794	0.836	0.995
12	2	Inside	0.87	0.725	0.872	0.979	1.0
13	2	Inside	0.9	0.774	0.920	0.992	1.0
14	2	Inside	0.94	0.813	0.949	0.997	1.0
15	2	Inside	0.97	0.844	0.967	0.999	1.0
16	2	Inside	1	0.870	0.978	0.999	1.0

An alternative method of fuzzifying the Antimony evidence is to use the continuous grid (ie. raw, unclassified Sb values). Using MI-SDM's fuzzification process, you could apply the Large function to log transformed Sb values and write out a new continuous grid.

Fuzzification Model

To create the fuzzy logic model shown in Figure 5 using geology (Geology_Grid with FM3) and antimony (Sb_ClassGrid with FM5), use the Fuzzy Logic menu selection with Gamma ($\gamma=0.9$) operator.

Additional evidential layers provided with the exercise can be used to create a more complex model that could involve other types of fuzzification and fuzzy operators. This model is purposely designed to take advantage of what was learned in the WofE model, but in real applications, a fuzzy-logic model would be considered when no training sites are available to develop a WofE model.

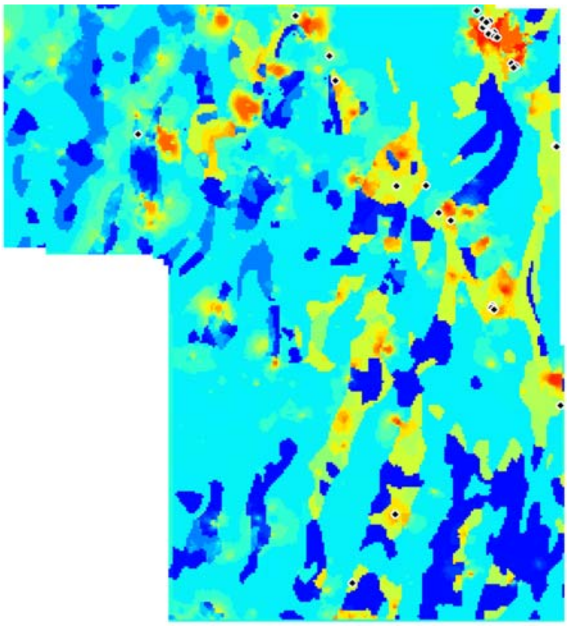


Figure 5 Fuzzy Gamma ($\gamma=0.9$) model using fuzzified geology and antimony

The fuzzy membership values are FM3 for geology and FM5 for antimony derived using the fuzzification process. The training points used for the WofE model are shown as black dots. The highest to lowest values are shaded from red to blue.

Guidance for an Artificial Neural Network Model

Poor results are obtained if categorical class values (eg. class value for geology) are input to the supervized artificial neural network analysis methods, as the artificial neural network software attempts to cluster by class value proximity. However, very useful results can be obtained with the artificial neural network by using fuzzy membership values as the inputs.

For the supervized neural network methods, a set of "non-deposits" or off-pattern training points is required. These can be created by generating random locations within areas of low probability in our previously created weights of evidence prospectivity map.

- Choose *Neural Networks > Generate Random Points* menu item.
- Select the weights of evidence prospectivity map as the ***Threshold layer***.
- Enter the prior probability (0.000587) as the ***Threshold value*** and WofE_PosteriorProbability as the ***Threshold column***.
- Accept the default number of points to create, which will be the same as the number of deposit training points.

MI-SDM will then create these points in random locations within the area defined by the threshold. You could also create points using a fuzzy logic prospectivity map to locate areas of low prospectivity. In this case, you would use a value of 0.5 for the threshold.

We now are ready to perform the artificial neural network analysis, using GeoXplore's RBFLN analysis method. Input to GeoXplore is a set of "vectors" which are the unique conditions for the specified evidential layers, with the same fuzzy membership values used for the fuzzy logic model.

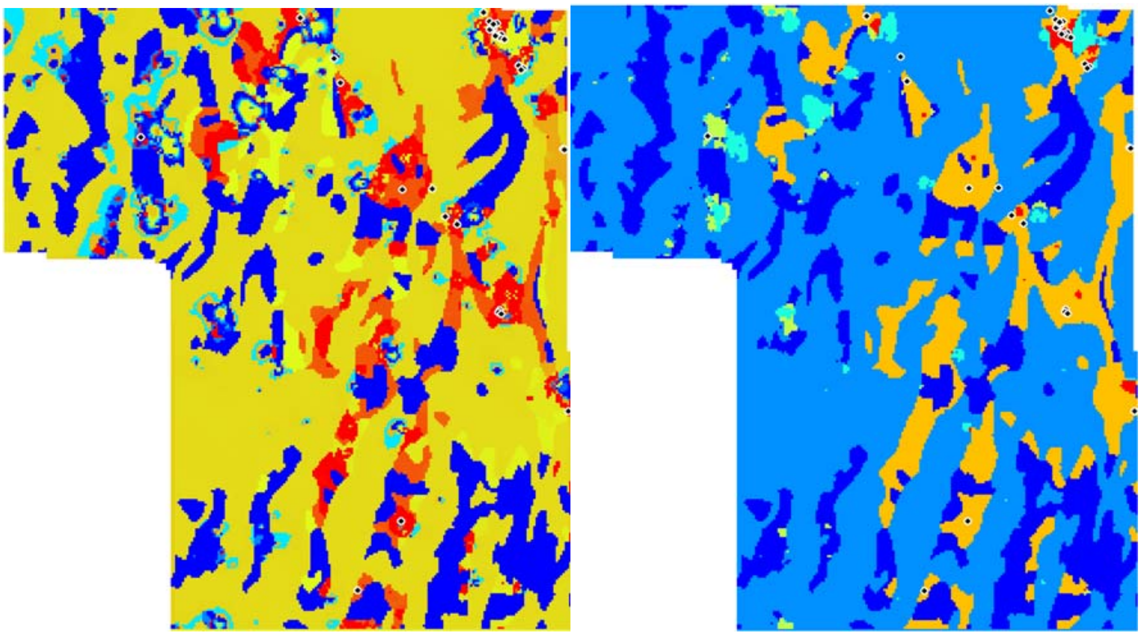
We can also use fuzzy membership values for the training points, which allows large deposits to be given more significance in the analysis than small deposits. The Carlin deposits layer has a column (FM) containing expertly assigned fuzzy membership values ranging between 0.75 and 0.95. The off-pattern training points do not have a fuzzy membership value and will all be assigned a value of 0.

To generate the neural network prospectivity map, we choose the ***Neural Networks > Neural Networks for Unique Conditions Grid*** menu item.

- Choose the ***RBFLN*** analysis method and choose the ***Create new Unique Conditions table*** option.
- Choose the correct point layer for off-pattern points, and set the fuzzy membership column for the deposit training points to FM.
- Choose Geology_Grid and Sb_ClassGrid as the evidential layers to analyze in the artificial neural network.

- Choose the correct ***Class Column*** (Class) and ***FM Column*** (FM2, or whatever you have called it) for each layer.
- From the RBFLN processing parameters screen, accept the default processing parameters and click the ***Train*** button. When training is complete, click the ***Classify*** button.
- When neural network classification is complete, click ***Return*** to display the unique conditions grid in MI-SDM, shaded by the neural network class. For more information on ***GeoXplore*** and neural network processing, refer to the on-line help or the references listed below.

You can also perform unsupervized ***Fuzzy Clustering*** using the same evidential layers. The results of the neural network processing using these data from the fuzzy model are shown in Figure 6.



A **B**

Figure 6 Supervized and unsupervized artificial neural network models

Prospectivity maps created from geology and Sb evidence using fuzzy membeship values created by fuzzification. Deposit training points shown as black dots for context.

A Prospectivity values have been generated using GeoXplore's RBFLN method. Prospectivity ranges from blue (low) to red (high).
B Unsupervized fuzzy clustering map. Colours do not directly indicate prospectivity, but all cells of the same colour as more similar to each other than they are to cells of different colours.

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