Fuzzy logic: Identifying areas for mineral development

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This article looks at the application of fuzzy logic set theory in GIS to identify potential areas for mineral development. Arc-SDM (Spatial Data Modeller) was used to assign fuzzy membership values to the selected criteria and calculate a combined output surface indicating the potential of areas for gold mineral development based on fuzzy set membership. Arc-SDM is a software extension for ArcMap that provides additional geo-processing and modeling functionality, including fuzzy logic tools for geological and mineral applications[1].

In classical set theory, founded by Georg Cantor (1843-1918), membership of a set is defined as either true (1)or false (0) [1]. An object can either belong to a set or not and there is no alternative option in between. This Boolean mathematical approach to classical set theory assumes that spatial data are precise in nature and that relationships are known exactly. In the real world, however, this is not always the case as there are often blurred boundaries and data may be continuous or imprecise. Classes are therefore not always homogenous with an exact clear start or end.

The theory of fuzzy logic was introduced by the mathematician Lotfi Zadeh in 1965 [2]. In fuzzy logic, membership of a set is expressed on a continuous scale from 1 to 0, where 1 represents full set membership and 0 represents full non-membership [3]. Data that do not fall completely into a set are assigned values between 0 and 1, representing their degree of membership. Fuzzy logic methodology is therefore seen to be more appropriate to model data, objects and knowledge that may be continuous, ambiguous or imprecise.

The creation of "fuzzy sets" allows the user to model more subjective factors. A set must first be defined, for example "the set of locations that have favourable gold mineral development potential" was defined for this study. All membership values

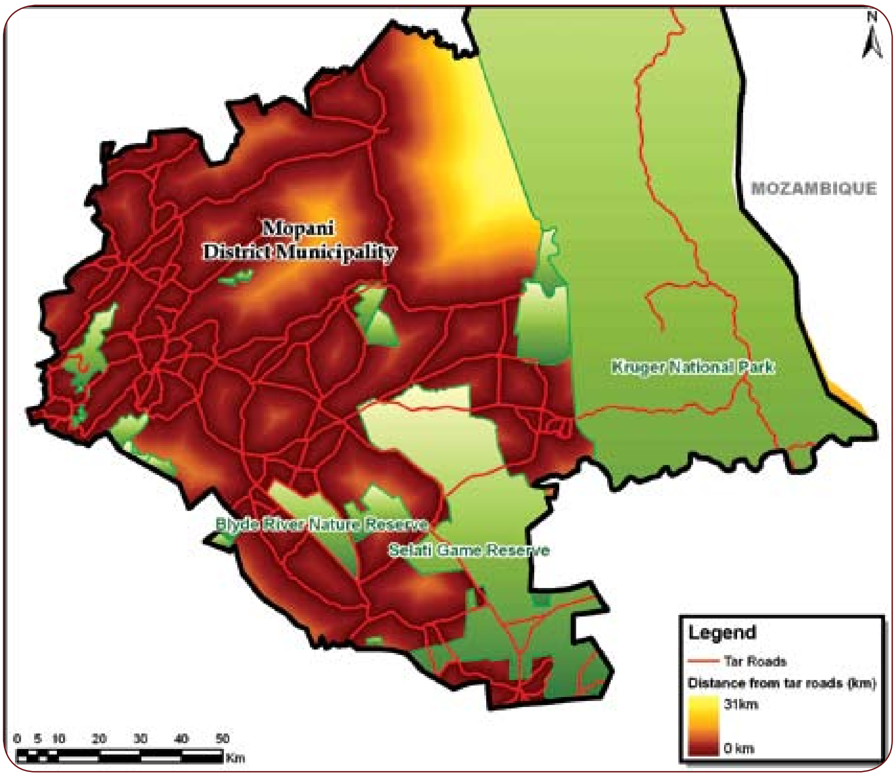

Fig. 1: Grid of distance from tar roads.

then refer to membership of this set. Fuzzy membership values must lie in the range from 0 to 1, however there are no practical constraints on the choice of values. Values are chosen to reflect the degree of membership of a set based on subjective judgment or the users' expert opinion [3].

The process of assigning fuzzy membership values to rank the data in terms of set membership is known as fuzzification. Mathematical functions may be used to transform the input data to the desired fuzzy membership in the interval (0,1). The shape of the function can be linear or take on any appropriate analytical or arbitrary shape [3]. Arc-SDM provides tools to define fuzzy membership functions including "linear", "small", "large", "near", "gaussian", and "mean-standard deviation" functions. The fuzzy membership functions can be previewed as a graph in Arc-SDM and applied to create a new raster grid of the fuzzy membership values.

Footnote 1: Arc-SDM was programmed by Don Sawatzky under the direction of Dr. Gary Raines of USGS (United States Geological Survey) and Dr. Graeme Bonham-Carter of the Geological Survey of Canada. Arc-SDM requires ArcGIS Spatial Analyst and can be downloaded from http://arcscripts.esri.com/details.asp?dbid=15341

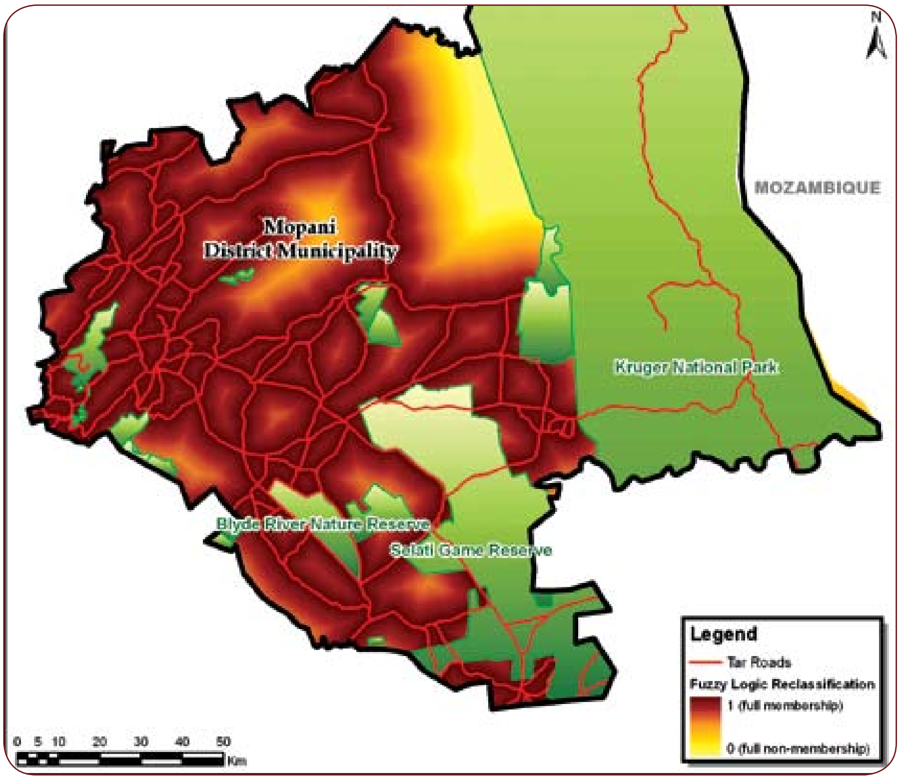

Fig. 2: Fuzzification of distance from tar roads.

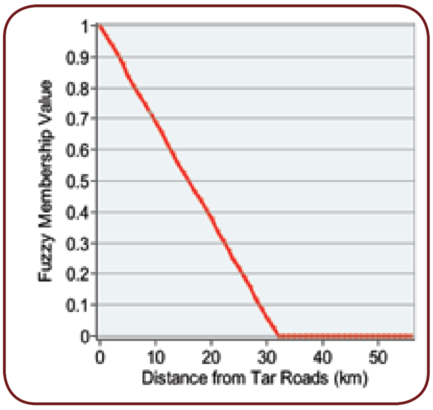

Fig. 3: Linear fuzzy membership function.

Analysis criteria

Various factors may impact on the suitability of an area for mineral development or mining, including the underlying geology, distance to other known mineral deposits, accessibility to transport, proximity to protected or sensitive areas, and distance to main places or towns.

The example below illustrates the application of fuzzy logic methodology to identify potential areas for gold mineral development in Mopani District Municipality in the Limpopo Province, based on the selected criteria.

Transportation

As transportation costs may impact on the economic viability of a mine, distance to roads and rail was regarded as one important criterion.

Spatial Analyst was used to calculate the straight line distance from main tar roads, as illustrated in Fig. 1. The values in the grid represent the distance from any given point in the study area to the nearest tar road.

A fuzzy membership of 1 (full membership) was then assigned to areas close to roads and 0 (full non-membership) to areas further away from roads, as indicated in Fig. 2. The fuzzy membership values in between 1 and 0 were calculated using a linear function, so that the fuzzy values gradually decrease the further the distance away from roads. The graph of the linear fuzzy membership function for roads is illustrated in Fig. 3. A similar procedure was followed with railway lines.

Existing gold mines and deposits

Distance to known gold mines and deposits was calculated as there is a greater chance of finding a potential source close to a known deposit. Fig. 4 depicts the GIS grid of distance from known deposits.

A fuzzy membership of 1 (full membership) was assigned to areas close to deposits and a fuzzy membership of 0,3 at 7 km from deposits, as illustrated in Fig. 5.

A "small" function was used to reclassify the distance to known deposits, as indicated in Fig. 6. Here smaller values of the crisp set are larger members of the fuzzy set. This is because there is a higher likelihood of finding gold close to a known gold deposit.

Geology

As certain deposits occur only in specific geological formations, the geology where gold may be found was selected out for the study area. Suitable geology for gold includes the Barberton, Witwatersrand, Pongola and Ventersdorp Supergroups as well as the Dominion Group.

Since the geology data are categorical, the "free data fuzzification table

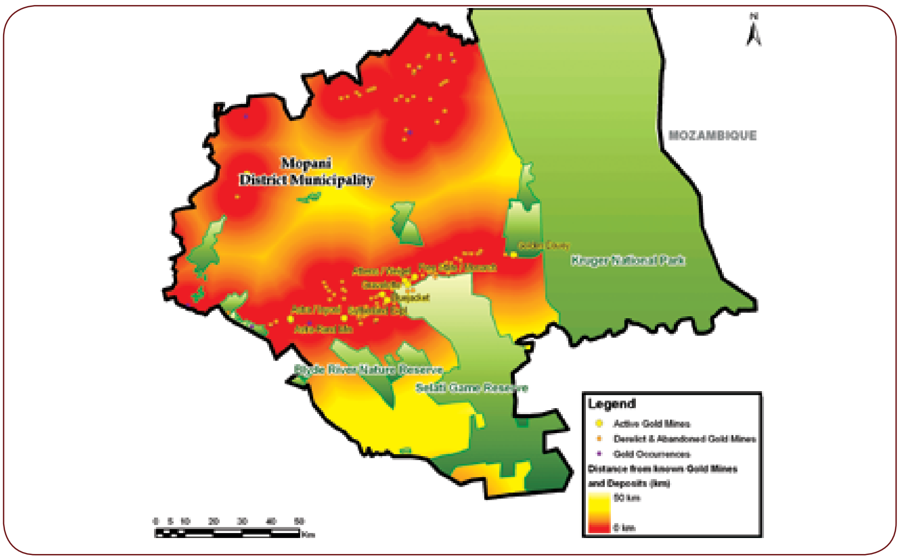

Fig. 4: Grid of distance from known deposits.

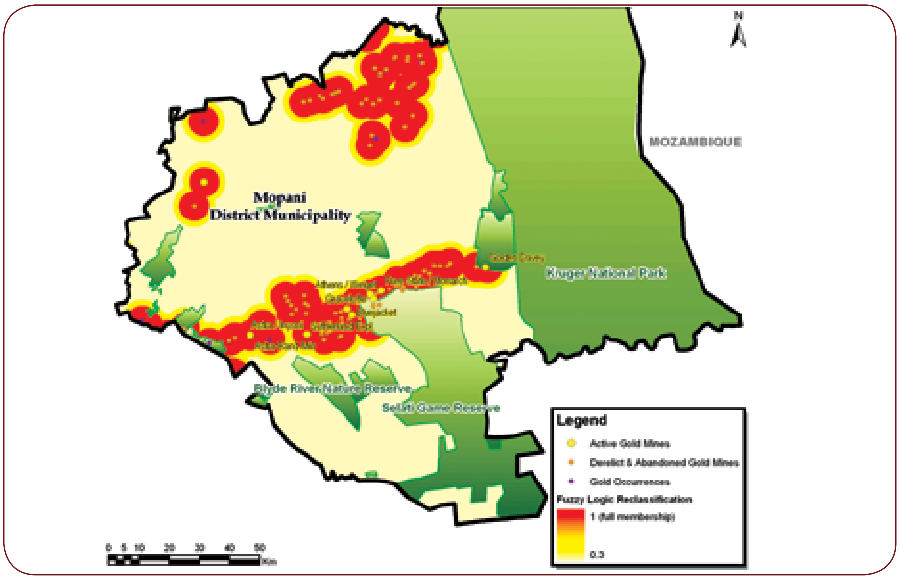

Fig. 5: Fuzzification of distance from known deposits.

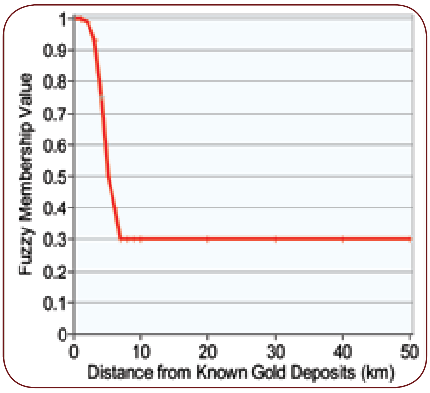

Fig. 6: "Small" fuzzy membership function.

method" was used in Arc-SDM. A fuzzy membership value of 0,7 was assigned to areas that fall within suitable geology, while a fuzzy membership value of 0,3 was assigned to areas that do not have suitable geology.

Main places

Distance from main places or towns was calculated due to the socio-economic aspects of mining such as labour and local economic development, as well as support linkages. Fig. 7 depicts the grid of distance from main places or towns in the study area.

A fuzzy membership of 1 (full membership) was assigned to areas close to main places and a fuzzy membership of 0,3 at 30 km from main places, as illustrated in Fig. 8. The fuzzy membership values in between 1 and 0 were calculated using a linear function, so that the fuzzy values gradually decrease the further the distance away from main places.

Sensitive areas

Sensitive areas such as environmentally protected areas, water bodies and urban settlements were merged together and assigned a fuzzy membership of 0 (full non-membership), as these areas are not suitable for mine development. Fig. 9 illustrates the sensitive areas that were assigned a fuzzy membership value of 0 in Fig. 10.

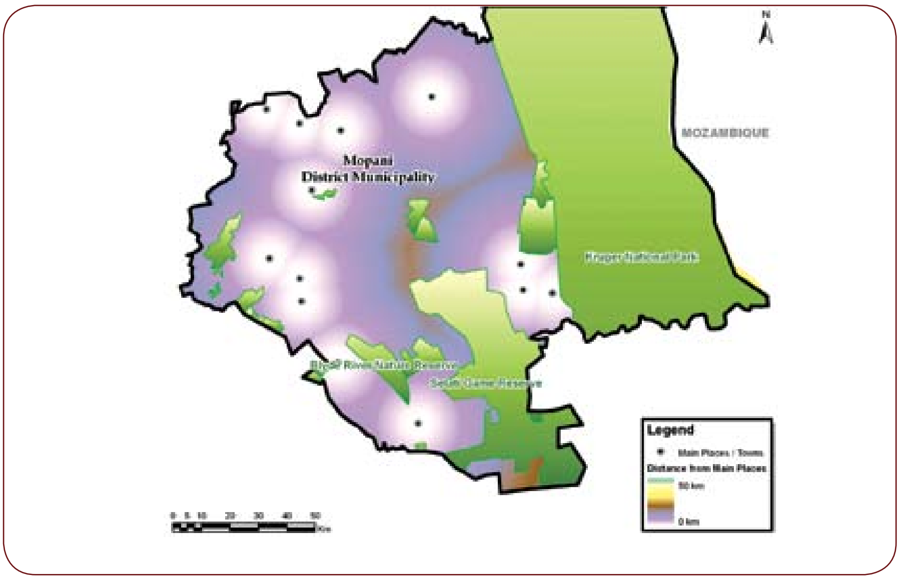

Fig. 7: Grid of distance from main places.

Combining criteria using fuzzy operators

The fuzzy logic evidential themes for the selected criteria were combined using the Arc-SDM fuzzy logic "calculator". Arc-SDM provides a variety of operators to combine fuzzy datasets, including fuzzy *And, Or, Algebraic Product, Algebraic Sum* and *Gamma Operators* [4].

The fuzzy OR operator uses the maximum value per cell out of the combination of evidential themes for the set. The combined output is therefore controlled by the maximum values of any of the input themes at a particular location. The combined membership value at a location is limited by the most suitable of the evidence maps. This operator may be suitable in cases where favourable indicators are rare and the presence of any positive evidence may be sufficient to suggest favourability [3]. A fuzzy OR operator was used to combine the fuzzy evidential road and railway themes, as access to either of these may be beneficial. The use of the fuzzy OR operator in the model is demonstrated in the process flow diagram in Fig. 11.

The fuzzy algebraic product operator multiplies the values of the input cells at the same location from the combination of evidential themes for the set. The combined fuzzy membership values tend to be very small with this operator, due to the effect of multiplying several numbers less than 1. All of the contributing membership values do however have an effect on the result [3]. A fuzzy algebraic product operator was applied between the sensitive areas evidential theme and the final combined output surface, as indicated in Fig. 11. Since sensitive areas were assigned a fuzzy membership value of 0 (full non-membership), the multiplication ensures that all sensitive areas have a final value of 0. Protected areas, water bodies and urban settlements are therefore indicated as unsuitable areas for mine development in the model.

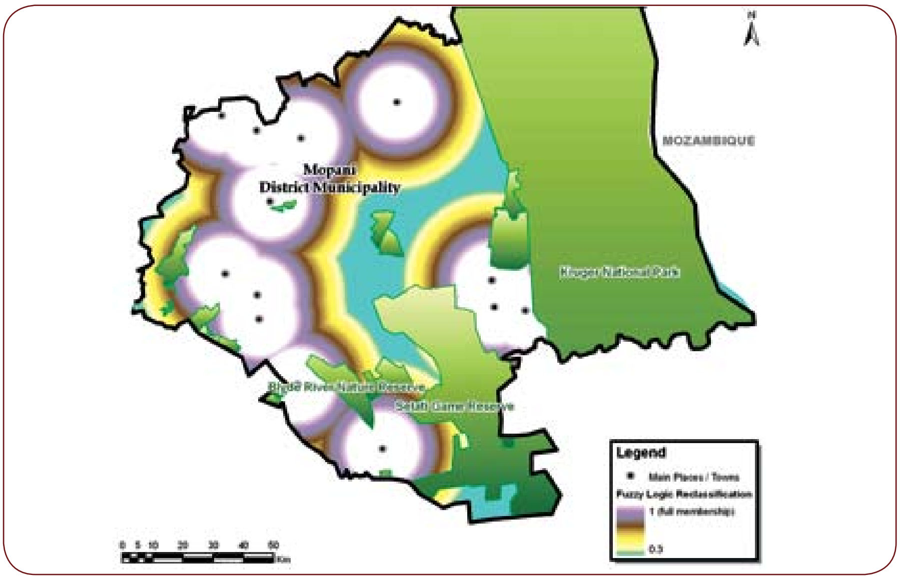

Fig. 8: Fuzzification of distance from main places.

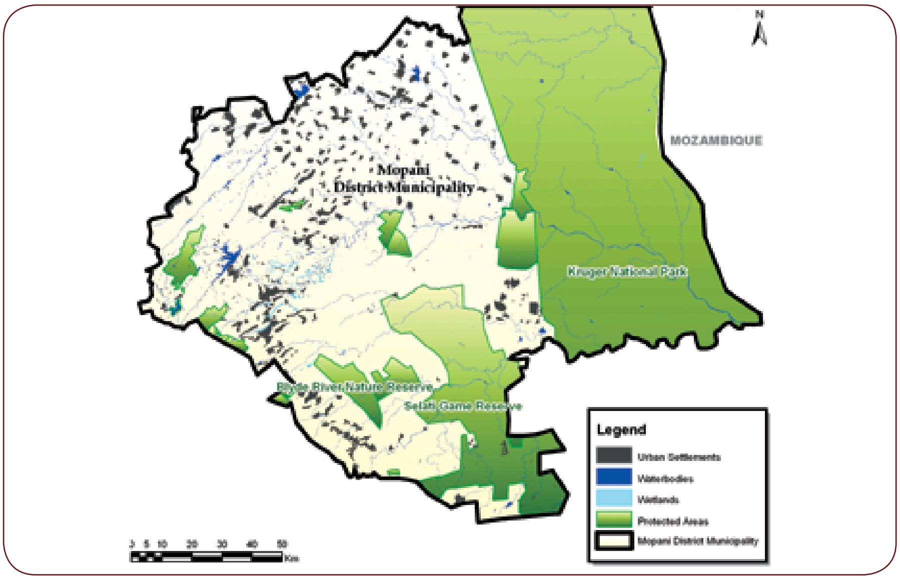

Fig. 9: Sensitive areas not suitable for mining.

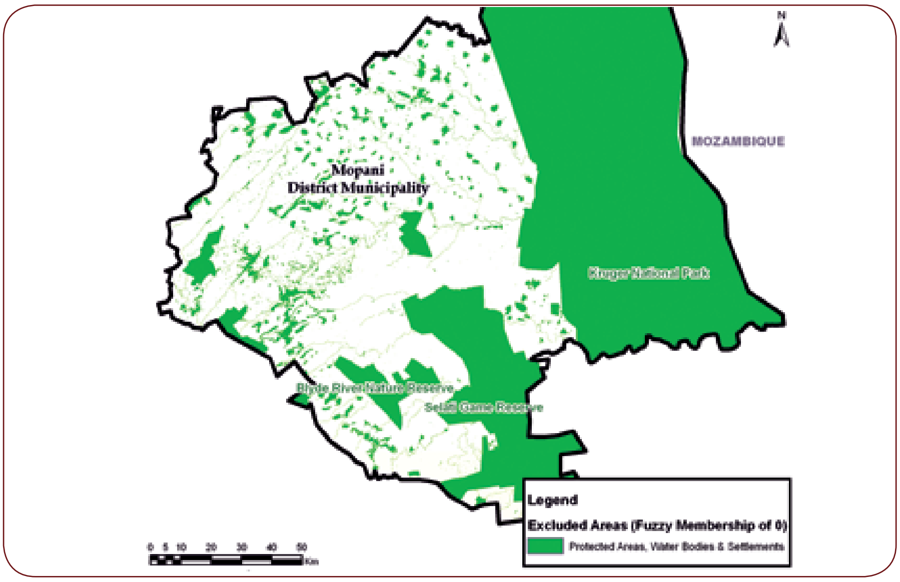

Fig. 10: Fuzzification of sensitive area data.

The fuzzy algebraic sum does not add all the values of the input cells, but rather subtracts the product of the difference between 1 and the cell input values, from 1. For example where *x* is the fuzzy membership value in grid one and *y* is the fuzzy membership value in grid two at the same location, the fuzzy algebraic sum is $1 - (1 - x)*(1 - y)$. Two pieces of evidence that both favour a hypothesis, reinforce one another and the combined evidence is therefore more supportive than either piece of evidence taken separately [3].

The fuzzy gamma operation uses both the fuzzy algebraic sum and fuzzy algebraic product with a parameter ratio between 0 and 1 selected by the user. When the parameter is 1, the combination is the same as the fuzzy algebraic sum; and when the parameter is 0 the combination equals the fuzzy algebraic product, while a parameter in between 0 and 1 produces output values that ensure a flexible compromise between the two [3].

A fuzzy gamma operation with a parameter of 0,7 was used to combine the fuzzy logic evidential themes for the remaining criteria in the gold potential study. The gamma operation is therefore dominated by the fuzzy algebraic sum, however the increasive effect is offset partially by the fuzzy algebraic product. The combined grid therefore takes all of the selected factors deemed important into consideration. The general conceptual fuzzy model used in the GIS is demonstrated in the flow diagram in Fig. 11.

The final combined output map in Fig. 12 indicates areas with a high membership of the set of locations that have favourable gold mineral development potential. The degree to which this proposition is satisfied is scored on a scale of 0 – 1 and then classified to make a map. The higher the value of the cell towards 1, the higher the potential for gold mineral development, based on the selected criteria. Known areas of gold occurrences are differentiated by the model and new potential areas are suggested for further field investigation. It should be noted that this analysis was undertaken as part of an academic study for local development planning purposes and the results should not

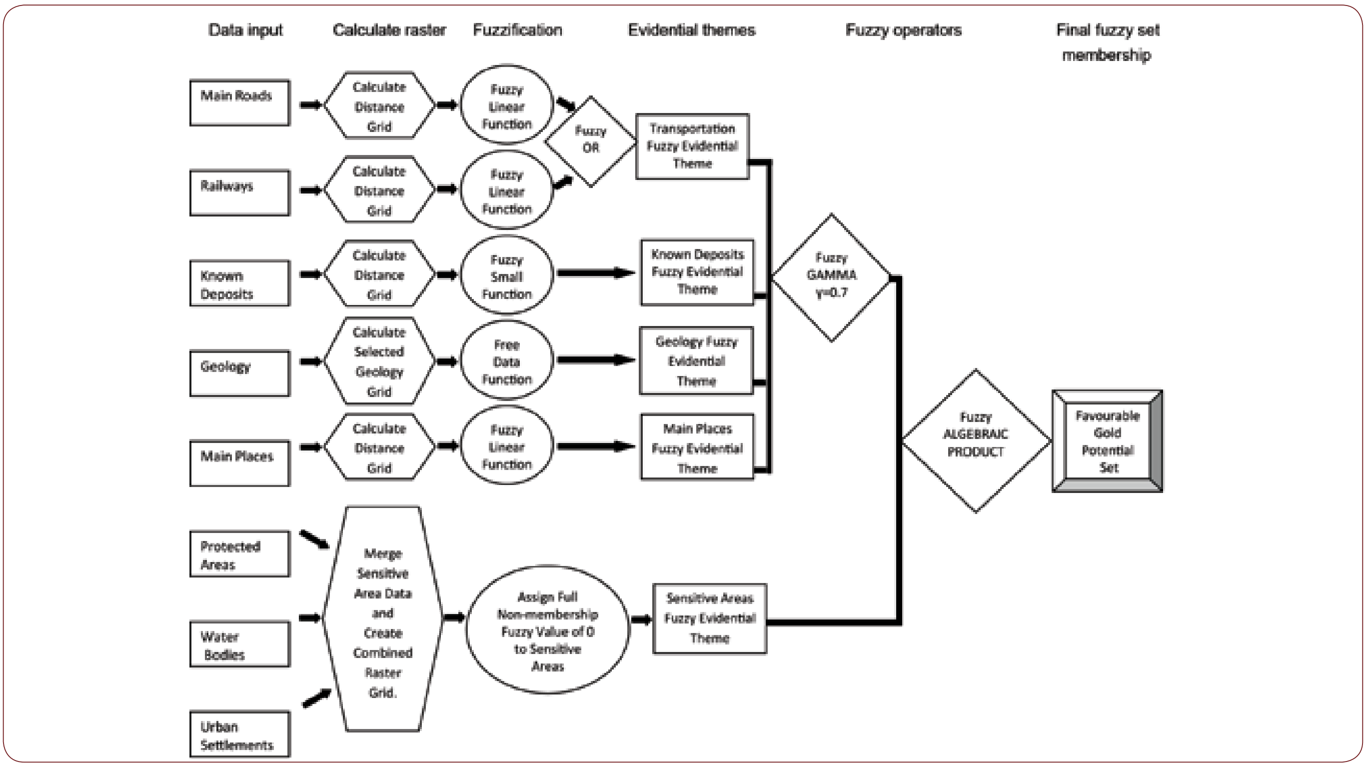

Fig. 11: Flow diagram of GIS fuzzy model.

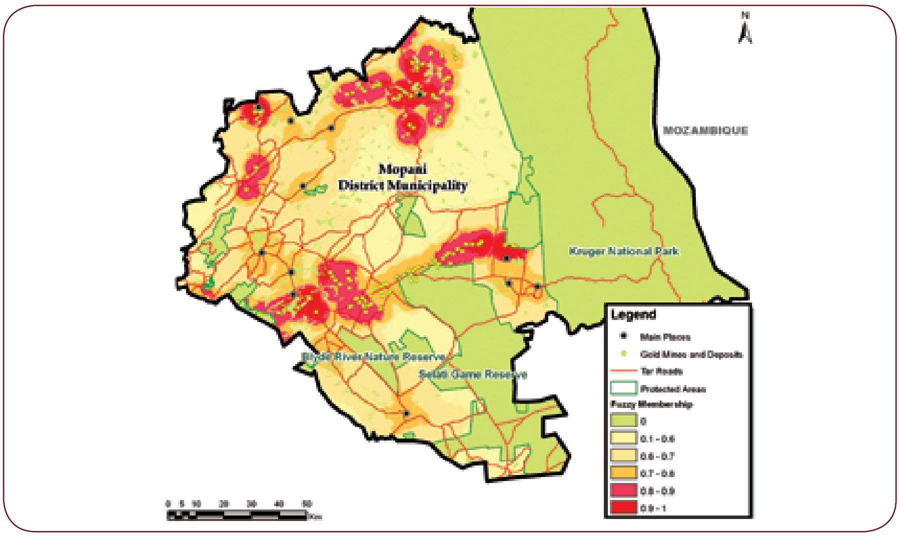

Fig. 12: Final fuzzy membership of the set of locations with favourable gold mineral development potential.

be considered for prospecting and exploration purposes without a more complete dataset and detailed analysis.

Acknowledgement

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