Performance Evaluation of a Developed Fuzzy-Based Model for Predicting Soil Degradation

Olumuyiwa Idowu Ojo, Atinuke Abidemi Olawoyin, Modupe Oluwakemi Akinyemi and Elijah Olusayo Omidiora

Faculty of Engineering and Technology, Ladoke Akintola University of Technology,

Ogbomoso, Nigeria

ABSTRACT

Soil degradation is a phenomenon that has always had an adverse effect on productivity of soil. It occurs when soil loses its quality as a result of human activities resulting from improper use usually for agricultural, industrial or urban purposes. Right from the beginning of human existence, soil has played a major part in human survival by being the backbone of Agriculture. But over the years, man's activities on the soil such as farming, use of fertilizers, deforestation, bush burning, etc. have all had adverse effect on the soil. Erosion has invariably led to degradation of the soil nutrients hence a necessity to monitor the rate and state of soil's degradation in order to take adequate measures it.

In order to achieve this, fuzzy model was used to predict the degradation after some factors have been quantified. Fuzzy model as an artificial intelligence technique has proven to be useful approach for addressing problems associated with simulating complex processes and environment in variety of Earth science disciplines. The model used was Fuzzy Based Dynamic Soil Erosion Model (FuDSEM). The model was used with different parameters and data to help its predictive ability. The results obtained from the output using the FuDSEM model shows that the area has low runoff potential. The results show that Fuzzy Logic model is reasonably accurate in predicting reliability of farm tractors. The fuel system was observed to be the most reliable of the tractor systems.

INTRODUCTION

Global warming and climate change has taken over the world and the fact that land degradation is the most important environmental issue has been ignored. Rising population is putting additional pressure on the land around the world and people are not aware of the economic, health and environmental influence of land degradation. Land degradation is an evolution that occurs when land loses its quality and productivity. Human activities and natural disasters are primarily responsible for land degradation. There are three main types of land degradation namely soil erosion, desertification, and salinization.

Soil erosion is one of the leading environmental problems of the world. In many areas, loss of this valuable natural resource takes place most imperceptibly, and slowly affects the long-term productivity of the land. Soil erosion also contributes to the degradation of the quality of surface and ground waters by adding transported sediments, nutrients, pesticides and increased turbidity.

Desertification can be caused by natural climate change that causes prolonged drought; human activities that reduce or degrade top land; increased population and livestock pressure on marginal lands; and deforestation. Desertification can lead to economic losses; prolonged drought; lower living standards and is a major threat to biodiversity.

Salinization is caused by high level of salt in the soil, over cultivation, irrigation mismanagement, and climate trends that favor accumulation. The consequences are: it stunts crop growth; lowers crop yield; destroys fertility and plants; damage to infrastructures and reduction of water quality.

Prediction is about how things will happen in the future. Land degradation prediction therefore entails using some parameters to determine the state of a land in the future. There are several models that have been used in the prediction of land degradation. The conventional methods for modeling are either empirical or process-based. Examples of the empirical models are Universal Soil loss equation (USLE), which was later developed to Revised Universal Soil Loss Equation (RUSLE), Modified Universal Soil Loss Equation (MUSLE). Examples of process-based models are the Water Erosion Prediction Project model (WEPP), Dynamic Water Erosion Prediction Project Model (DWEPP), European Soil Erosion Model (EUROSEM) (Mitasova *et al*., 1996; Yitayew *et al.,* 1999).

To address some of the problems associated with conventional modeling, several erosion models have made use of Artificial Intelligence (AI) technologies. AI has developed rapidly in recent years providing sophisticated tools to simulate complex environmental processes (Tayfur and Singh, 2006; Svoray *et. al*., 2007). Among AI technologies, one of the most promising is the Fuzzy logic. It proposes a mathematic calculus to translate the subjective human knowledge of the real processes. It is a way to manipulate practical knowledge with some level of uncertainty. The fuzzy sets theory was initiated by Lofti Zadeh in 1965. The behavior of such systems is described through a set of fuzzy rules, like: IF <premise> THEN <consequent> that uses linguistic variables with symbolic terms. Each term represent a fuzzy term. Land degradation, is a major threat to the environment and which also affects the economy of that area. Areas of land degradation need to be identified and appropriate conservation measures implemented. Prediction of land degradation therefore becomes necessary as a method of conservation and there is a need for emerging nations to develop simple methods for predicting areas of extensive land erosion using imprecise, but real-world input data at least cost with considerable accuracy. The study thus aimed at evaluating the performance of both fuzzy and neuro-fuzzy models in predicting land degradation. Due to the importance of land to human life (as it provides food) and to the society (as it provides land and housing), it becomes important that land degradation (erosion) should be avoided as much as possible. Therefore, if it can be predicted the problem can be avoided and mitigation measures be taken against it.

Fuzzy Systems

Fuzzy logic was introduced by Zadeh in 1965 to represent or manipulate data and information possessing non-statistical uncertainties. Fuzzy logic as an artificial intelligence technique has proven to be a useful approach for addressing problems associated with simulating complex processes and environment in a variety of Earth Science disciplines (Zhu *et. al*., 1996; Tayfur and Singh, 2006; Svoray *et. al*., 2007). The prime advantages of fuzzy logic are its ability to represent and process uncertain data in the form of moderately continuous classes (Metternicht, 2001); to efficiently model processes with indeterminate boundaries (Burrough, 1996); and to facilitate more flexible knowledge-based modeling developments. These capabilities enable fuzzy logic to deal with imprecise and uncertain data and relationships allowing modelers to use inherent dependencies on empirical features when designing a model.

Types of Fuzzy Models

There are three major types of fuzzy models and they are: linguistic fuzzy model, Fuzzy relational model and Takagi-Sugeno model. Also, there are other categories of fuzzy models as described by Pedryez and Gomide (2007). They are tabular fuzzy models, rule-based fuzzy models, and fuzzy relational models including associative memories, fuzzy decision trees and fuzzy neural networks and fuzzy cognitive maps (Pedryez and Gomide, 2007). In land sciences, fuzzy logic is traditionally used to improve the spatial classification of various land features such as land stability (Burrough *et. al.,* 1992). Land erosion modeling has also been addressed with fuzzy logic in a variety of procedures and to various degrees. Some studies have used the proven ability of fuzzy logic in spatial classification of lands to improve the spatial characteristics of a given model, such as the USLE (Ahmad *et. al*., 2000). Others have modified a model (e.g. the RUSLE) to fit the fuzzy logic approach thereby improving its performance and overcoming issues of uncertainty, while increasing model flexibility and realistic description of the relationships between its parameters. Fuzzy logic algorithms have been successfully employed in several hydrological watershed management studies (Tayfur *et. al*., 2003). They have also been used for designing a simple catchment land erosion model (Mitra *et. al*., 1998) which has proved to be used in applications with low quality inputs. Most of the related studies have indicated that fuzzy logic is a flexible and easy-to-apply approach, a vital benefit for both modelers and end-users. The need for further improvement of fuzzy logic based erosion model is noted in many publications. The advantage of using fuzzy logic for erosion modeling was suggested in the discussion of the MEDRUSH, physically-based, catchment-scale model (Kirkby and McMahon, 1999). A simple fuzzy logic sediment transport model was compared to a physically-based model, showing that fuzzy-logic despite its various advantages, cannot replace a physically-based model (Tayfur *et. al.,* 2003). There is therefore a need for the development of a more physically-based fuzzy logic model to address these issues, a simple and easy-to-apply catchment-scale land erosion model is introduced, designed for catchment interface and management purposes by: (1) using relatively common input data; (2) having a modular model structure; and (3) a clear and easily interpretable output analysis, by producing possibility or potential rather than quantitative erosion maps. The model is FUDSEM (Fuzzy-based Dynamic Land Erosion Model). FUDSEM is explicit and temporarily dynamic and is formalized and based on fuzzy logic equations. FUDSEM was initially evaluated on a small data-rich catchment and was found well calibrated; it was then evaluated on a medium-sized heterogeneous catchment in a catchment in central Israel. Initial evaluations of the model-scale were conducted by: (1) comparison of FUDSEM run-off predictions against measured run-off from five hydrological stations and (2) a site specific evaluation of the FUDSEM multi-year erosion prediction in two sub-catchments. FUDSEM was compared with two other erosion models (a temporarily static version of itself and a known physically-based model). The results showed the advantages of FUDSEM over the other two models in evaluating the relative distribution of erosion, thereby emphasizing the benefits of its temporarily dynamic and fuzzy structure. Catchment-scale erosion modeling is particularly desirable, since it facilitates more efficient land erosion conservation planning (De Jong *et. al*., 1999) by providing spatial data over large areas, data that may be used to decrease erosion related problems (Jetten *et. al*., 2003). The potential of such models for erosion for environmental management and planning is clear, but most state-of-the-art land erosion models are difficult to apply over large areas due to intensive detailed and data requirements (Meritt *et. al.,* 2003).

Several large scale erosion models such as WEPP (Nearing *et. al*., 1989), EUROSEM (Morgan *et. al*., 1992), LISEM (De Roo *et. al*., 1996), EROSION 3D (Schmidt *et. al*., 1999), and MEDRUSH (Kirkby and McMahon, 1999) have been reported and examined. Despite their important contribution to understanding, quantifying and predicting land erosion, most models do not reliably predict erosion yield over large heterogeneous areas (Trimble and Crosson, 2000). The most prominent reasons for this lack of reliability are: (1) insufficient input data with high spatial and temporal resolution; (2) insufficient calibration (Folly *et. al*., 1999); and (3) uncertainty associated with model parameters (De Roo, 1998). Few erosion models have been developed to continuously simulate the erosion process over long periods, because they do not incorporate temporally dynamic variables such as vegetation growth and ground water dynamics (Jetten *et. al*., 1999). In recent years, some of the models that address some of the problems described above have been published. For example, SEDEM (Van Rompaey *et. al.,* 2001) uses the empirical RUSLE as a simple erosion rate platform in a spatially distributed model and is to address low-detail distribution data in large catchments. Despite its simplicity, the model accurately calculates sediment delivery but the empirical RUSLE requires intensive calibration. Temporally, dynamic erosion calculations have been addressed by a variety of landscape evolution models, such as SIBERIA (Willgoose *et. al.,* 1991), GOLEM (Tucker and Slingerland, 1994), LAPSUS (Schoorl *et. al*., 2000), CHILD (Tucker *et. al.,* 2001) and CAESAR (Coulthard *et. al*., 2002). Such landscape evolution models successfully simulate the spatial and temporal distribution of sediment, but are usually complicated to operate and analyze; moreover, detailed input data and outstandingly powerful computers are required. In general, the advantages of fuzzy systems are many.

METHODOLOGY

Fuzzy Based Dynamic Soil Erosion Model (Fudsem)

Fuzzy logic provides a systematic tool to incorporate human experiences. It is based on three core concepts namely; fuzzy sets, linguistic variables and possibility distributions. Fuzzy set is used to characterize linguistic variables whose values can be described qualitatively using a linguistic expression and quantitatively using a membership function (MF). Linguistic expressions are useful for communicating concepts and knowledge with human being whereas membership functions (MF) are useful for processing numeric input data. When a fuzzy set is assigned to a linguistic variable, it imposes an elastic constraint called a possibility distribution on the possible values of the variable. Fuzzy logic is a rigorous mathematical discipline while fuzzy reasoning is a straight forward formalism for encoding human knowledge or common sense in a numerical frame work. As a theory in formal mathematics, it enables a definitive solution to be obtained for problems that are complex, uncertain and unstructured (Bojorquez-Tapia *et. al*., 2002). A general fuzzy system is composed of three primary elements; fuzzy sets membership functions (mfs) and fuzzy production rules. A fuzzy set A may be defined as follows (Burrough *et. al.,* 1992):

For each $A = \{X, \mu A(X)\} x E X$ (1)

where X = {x} is a finite set of points and μA(x) is the membership of x in A

The membership function describes the variable's membership assigned to A and therefore it may quantify the influence of the variable x on the predicted phenomenon as it is grasped by the developer (Burrough and McDonnel, 2000). To integrate the effects of a number of variables, several membership functions can be merged in a variety of joint membership functions (JMF). Both membership and joint membership functions provide a simple membership grade in a range 0-1, where 1 is full membership and 0 is no membership. In FUDSEM, the term 'potential' is used to describe this mathematical grade; using more process- related terminology. For instance, run-off potential means that the membership grade has a high possibility of run-off development. In general, FUDSEM predicts the hillslope soil erosion potential for each day that exceeds a user-defined precipitation depth value in meteorological data base. It is based on the infiltration excess run-off mechanism on hillslopes; with emphasis on the temporal dynamics of this process. FUDSEM divides the erosion process into a sequence of four sub-routines including: Antecedent condition of soil moisture, Runoff generation, Transport capacity and Soil erosion. Using fuzzy logic, each subroutine is calculated by an individual JMF that combines the relevant parameters (represented by membership functions). It is executed as follows:

i. Soil moisture potential (JMF1) is explicitly calculated;
ii. Run-off potential (JMF2) is calculated by considering the soil moisture potential;
iii. Run-off potential is spatially accumulated, based on digital elevation model data (DEM);
iv. Run-off transport capacity potential (JMF3) is calculated, based on the accumulated Run-off potential;
v. Soil erosion (JMF4) is calculated, based on the transport capacity potential; and
vi. The model proceeds to the next day in the metrological database, until we reach the last day in the wet season.

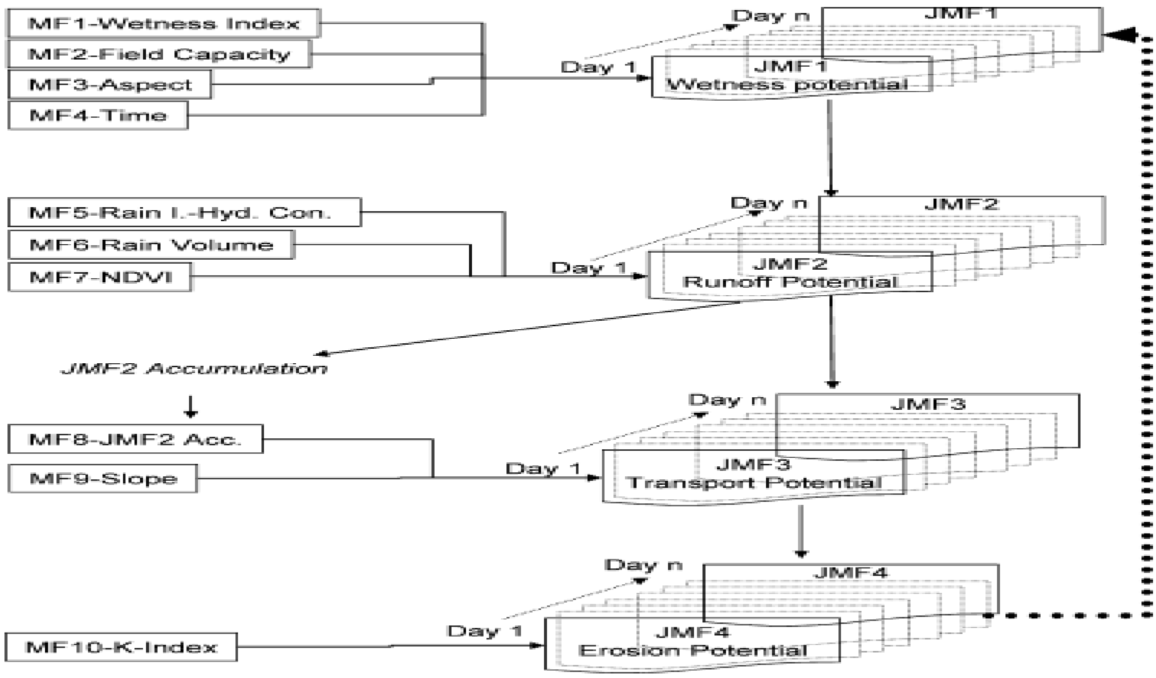


Figure 1: FuDSEM flow chart

From Figure 1 FUDSEM operates in daily intervals divided into four subroutines, each calculated by distinct JMF. All model parameters are represented in membership functions, converting their values into a membership score assigned to the relevant set. JMF1 represents the cell moisture potential that acts as input parameter; JMF2 represents the cell Run-off potential which is spatially accumulated, based on a flow direction layer. The original and accumulated Run-off potential acts as input parameters in JMF3 calculation, which is the Run-off sediment transport capacity. JMF3 acts as an input parameter in the final subroutine which is the calculation of a cell's erosion potential (JMF4). After producing the erosion potential map, FuDSEM advances to the next day on the database and recalculates the four subroutines with the new values. The functions and weights used in FUDSEM are the outcome of generalized interpretation of common knowledge of erosion processes. Unlike standard physically-based models, the weights are not intended to represent an accurate quantitative relationship between the parameters, but to provide a general interpretation as envisaged by the modeler (Baja *et. al*; 2002; Robinson, 2003). This is acceptable since the model predicts the potential of the parameters, thus representing its relative spatial and temporal distribution, rather than providing a quantitative prediction of erosion yield. Therefore, the relationship between the parameters i.e. functions and weights are not directly linked to specific study, but were chosen through a combination of information taken from the relevant literature and expert knowledge.

Soil Moisture Potential (JMF1)

Antecedent soil moisture conditions are an important parameter in runoff generation. They may vary considerably over time (Jetten *et al.*, 1999), especially in semi-arid environments characterized by scattered rainfall events. FuDSEM estimates soil moisture conditions by linking four parameters: (1) time elapsed from the previous rainfall event (Te); (2) wetness index (WI; Barling *et al.*, 1994); (3) hillslope aspect (SA); and (4) soil field capacity (FC). The membership functions assigned to the parameters in this sub-routine represent the membership score for the high soil moisture conditions set (A_1). The membership score of Te assigned to A_1 is calculated, using the 'left shoulder sigmoidal' membership function (Robinson, 2003; Figure 2d) generally described by:

$$\mu A_i = \frac{1}{1+e^{\beta(x-\alpha)}} \quad (2)$$

where α is the mid membership value of x and b is the function slope. The left shoulder sigmoidal function was chosen on the basis of the exponential ratio in soil moisture decrease with time (Hillel, 1998). The function parameters (α and β listed in Table 1), were estimated, based on expert knowledge.

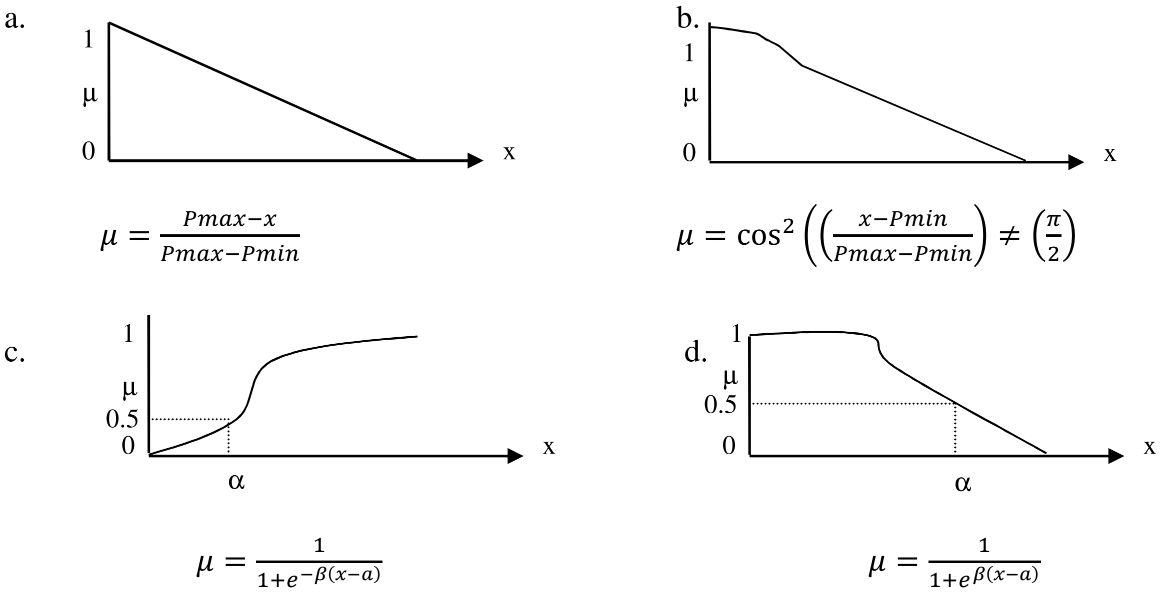


Figure 2: Schematics of four membership functions used in FuDSEM: (a) linear (Robinson, 2003); (b) sigmoidal (Urbanski, 1999); (c) left shoulder sigmoidal (Robinson, 2003); (d) right shoulder sigmoidal (Robinson, 2003).

The wetness index is a widely used equation, based on division of the cell slope by its contributing area;

$$WI_i = L_n\left[\frac{As_i}{tan\beta_i}\right] \quad (3)$$

Where: As_i = upper drainage area of a given cell (1) m^2, β = the gradient of the cell in degrees (Barling *et. al.*, 1994).

Natural logarithms are used to avoid the large numbers that may be produced in large drainage areas. High WI values indicate a higher membership score assigned to the set A_1. The WI membership score assigned to A_1 is calculated by a mirror version of the sigmoidal membership function (Urbanski, 1999) generally described by Eq. (4)

$$\mu A_i = cos^2\left(\frac{(x-p_{max})}{(p_{max}-p_{min})}\frac{\pi}{2}\right) \quad (4)$$

Table 1: Summary of FuDSEM parameters

JMF	Factor	Membership Function Type	α	β	P_{min}	P_{max}
1.	Wetness index	Sigmoidal			0	0.32
	Aspect	Sigmoidal			0	360
	Field capacity	Linear			6.1	42
	Time	Left shoulder	2	1		
2.	Infiltration Excess	Sigmoidal			0	2000
	Rain depth	Sigmoidal			0	40
	NDVI	Linear			0	0.95
3.	Accumulation	Linear			0	10
	Slope	Right shoulder	30	0.1		
4.	k-index	Linear			0.33	0.52

The hill-slope aspect represents the influence of solar radiation flux on soil moisture as a function of aspect azimuth. In the northern hemisphere, south-facing slopes are commonly less humid, due to higher solar exposure (Oliphant *et. al.*, 2003). Therefore, the SA membership score assigned to A_1 increases as a function of radial distance from a 180 degrees aspect azimuth. Based on Svoray *et. al.* (2004), the membership score of SA assigned to A_1 was calculated using a sigmoidal membership function (Urbanski, 1999) generally described by the following equation:

$$\mu A_i = cos^2\left(\frac{(x-p_{min})}{(p_{max}-p_{min})}\frac{\pi}{2}\right) \quad (5)$$

where x is the input value and p_{min} and p_{max} are the minimum and maximum values of the variable x.

The function's parameters ($p_{max} and\ p_{min}$), listed in Table 1 are based on the values reported in Svoray *et al.* (2004). The effect of soil characteristics on soil moisture is represented by the field capacity of the soil in each cell. The water holding capacity of the soil varies considerably with soil texture, organic matter content and other physical characteristics (Hillel, 1998). Thus, high FC values increase the cell membership assigned to the set A_1. Based on De Jong (1994) and Svoray *et. al.* (2004) the membership score is described by a mirror version of the linear membership function (Robinson, 2003) generally described by the following equation:

$$\mu A_i = -\left(\frac{p_{min}-x}{p_{max}-p_{min}}\right) \quad (6)$$

The function parameters (P_{max} and P_{min}) are simply the maximum and minimum values of the database. The JMF, combining the soil moisture potential parameters, which were formulated with the 'No Trade Off' (NTO) convex combination JMF (Urbanski, 1999) generally described by;

$$\text{JMF} = \left(\sum_{j=1}^{m}\lambda_j\mu_{A_j}\right) \wedge \left(\sum_{j=1}^{n}\lambda_j\mu_{A_j}\right) \quad (7)$$

Where $\lambda_{1,\ n}$ are the weights of the membership functions and ^ is the minimum between the two groups of membership functions. This operator was chosen on the assumption that if sufficient time has passed since the last rainfall event, the top soil will dry out regardless of any other parameters. Under these conditions, the dominant parameter influencing the soil moisture potential is Te; thus, if Te = 0, then JMF1 = 0. The weight assigned to Te in the JMF is double that of the other parameters, due to its important role in the moisture loss process in semi-arid regions. All the other parameters were assigned an equal weight, under an assumption of equal contribution to the soil moisture potential. The final soil moisture potential JMF is presented in the following equation:

$$JMF1 = \begin{cases} 0.0 & Te = 0 \\ 0.4Te + 0.2SA + 0.2FC + 0.2WI \end{cases} \quad (8)$$

Run-Off Potential (JMF2)

The daily runoff potential is simulated only in cells with infiltration excess. Cells with no excess infiltration are assigned a zero runoff potential. Calculating the runoff potential for a cell with excess infiltration is undertaken by joining four parameters: (1) Soil moisture potential (JMF1); (2) Excess infiltration (IE); (3) Daily rainfall depth (RD); and (4) Vegetation cover (NDVI – normalized difference vegetation index; Tucker, 1979). The membership functions assigned to the parameters in this sub-routine represent the membership score of the set of highest runoff generation potential (A_2). The value of JMF1 represents the cell membership assigned to A_2, under the assumption that high soil moisture content increases the possibility for runoff generation. Excess infiltration is calculated by subtracting the saturated hydraulic conductivity of the soil from the daily rainfall intensity. The mirror version sigmoidal membership function (Urbanski, 1999) is used to convert the excess infiltration values into the membership score assigned to A_2, based on the relationship described in Moody and Martin (2001) and Valmis *et al.* (2005). The function parameters (P_{max} and P_{min}), listed in Table 1, are simply the maximum and minimum values of the database. Based on the relationship reported in USDA-SCS (1985), the membership score of daily rainfall depth of A_2 is described by the mirror version sigmoidal membership function (Urbanski, 1999; Eq.(4)). Vegetation cover affects runoff generation by decreasing raindrop energy and increasing its infiltration rate (Yair and Kossovsky, 2002; Calvo-Cases *et. al*., 2003). Vegetation cover in semi-arid regions is characterized by patchy and heterogeneous distribution, creating a high spatio-temporal variability in water redistribution along the hill slopes (Svoray and Shoshany, 2004). Based on FAO (1967), the membership score of NDVI assigned to A_2 is calculated by a linear membership function (Robinson, 2003; Figure 2a), which is generally described by the following equation:

$$\mu A_i = \frac{P_{max} - x}{P_{max} - P_{min}} \tag{9}$$

Combining the four membership functions, the calculation of the overall runoff potential is carried out with the NTO JMF (Urbanski, 1999; Eq. (7)), in order to introduce IE as a threshold parameter. As mentioned above, negative or zero IE values yield zero runoff potential. The weight assigned to NDVI is double the weight assigned to the other parameters due to its importance in semi-arid environments (Yair and Kossovsky, 2002). All other parameters were assigned an equal weight under the assumption of equal contribution to runoff potential. The final runoff potential JMF2 is presented in the following equation:

$$JMF1 = \begin{cases} 0.0 & Te = 0 \\ 0.4Te + 0.2SA + 0.2FC + 0.2WI & \end{cases} \tag{10a}$$

$$JMF2 = \begin{cases} 0.0 & IE \leq 0 \\ 0.2IE + 0.2RD + 0.4NDVI + 0.2JMF1 + & IE > 0 \end{cases} \tag{10b}$$

Transport Capacity (JMF3)

The ability of runoff to transport sediments is influenced by a variety of parameters; among them shear stress, vegetation cover and soil and topographic characteristics (Thornes, 1980). The initiation of erosion and transport of sediment by water is performed on hill slopes by unconcentrated runoff and by rill flow. Further downstream, it occurs in and forms gullies and channels. No distinction is made between these in our FuDSEM model, which is acceptable in non-mechanistic models (Hillel, 1998). Three parameters are linked to calculate the runoff transport capacity potential in the model: (1) Run-off potential (JMF2); (2) Run-off accumulation (Acc); and (3) Local slope decline (S). The membership functions assigned to the parameters in this sub-routine represent the membership score assigned to the set with the highest run-off transport capacity potential (A_3). Runoff potential (JMF2) represents the cell membership score of A_3, under the assumption that a high value of run-off increases cell transport capacity. Run-off volume and transport capacity in a given cell are influenced by the runoff generated in situ and by run-off accumulated from its upslope contributing area. Accumulation to a given cell (Acc) is influenced, not only by the contributing area, but also by land cover characteristics of the accumulating catchment. A cell with high run-off potential is regarded as a source for the down-slope cells, while, by contrast, a cell with low run-off potential is considered a sink. Therefore, the runoff accumulation procedure is important for describing the spatio-temporal dynamics of runoff flow. The Acc. membership function assigned to A_3 is described by the mirror linear function (Robinson, 2003; Eq. (6)). Slope represents the effect of gravitational force on runoff discharge. A steep slope increases runoff discharge, resulting in a higher transport capacity. Based on De Jong *et al.* (1999), we used the 'right shoulder sigmoidal' membership function (Robinson, 2003; Fig. 2c) to describe the membership score of slope ofA_3, as follows:

$$\mu A_i = \frac{1}{1+e^{-\beta(x-\alpha)}} \quad (11)$$

The parameters α and β (Table 1) were evaluated from the results of a small pan experiment (Kirkby, 1980). Combining the three membership functions to calculate the transport capacity potential is undertaken with the 'convex combination operation function' (Burrough *et al*., 1992), which is generally described by:

$$JMF = \lambda_1\mu_{A1} + \lambda_2\mu_{A1} + \cdots + \lambda_n\mu_{A1} \quad (12)$$

The three parameters were assigned equal weights in the final transport capacity potential JMF, under an assumption of equal contributions to the process

$$JMF3= 0.33S+0.33Acc+0.33JMF2 \quad (13)$$

Soil Erosion Potential (JMF4)

The final sub-routine calculates the erosion potential by assuming that in a specific transport capacity, the entrainment of sediments is a function of topsoil erodibility: sediment entrainment and thus, erosion are expected to increase in more erodible soils. Therefore, the daily erosion potential is calculated by linking the runoff transport capacity (JMF3) with K, the soil erodibility index (Wischmeier and Smith, 1978). The membership functions assigned to the parameters in this sub-routine represent the membership score to the highest erosion potential set (A_4). JMF3 represents the effect of high transport capacity on the overall erosion potential and K represents topsoil sensitivity to erosion. A high value of erodibility results in higher erosion potential for given runoff conditions. The membership score of K, assigned to A_4, is described by the mirror version linear membership function (Robinson, 2003; Eq. (6)) and based on Mitra *et. al.,* (1998). Combining the two membership functions to calculate the erosion potential is undertaken with the 'convex combination operation functions (Burrough *et. al.,* 1992; Eq. (12)). We assume that the transport capacity potential dominates the final erosion calculation, so we assign it a considerably higher weight than K. The erosion potential JMF is represented by

$$JMF4 = 0.1K + 0.9JMF3 \quad (14)$$

RESULTS AND DISCUSSION

Fuzzy Based Dynamic Soil Erosion Model (FuDSEM), under fuzzy logic model was used in the prediction of soil erosion and evaluations were made using the results from the model. The result of the prediction was obtained from the value of JMF4 from day one to day 30. The results show that the area used for the prediction has low erosion potential. The set of data for this work was gathered based on expert knowledge and from predictions carried out previously on soil erosion.

Journal of Environment and Earth Science
ISSN 2224-3216 (Paper) ISSN 2225-0948 (Online)
Vol.5, No.21, 2015

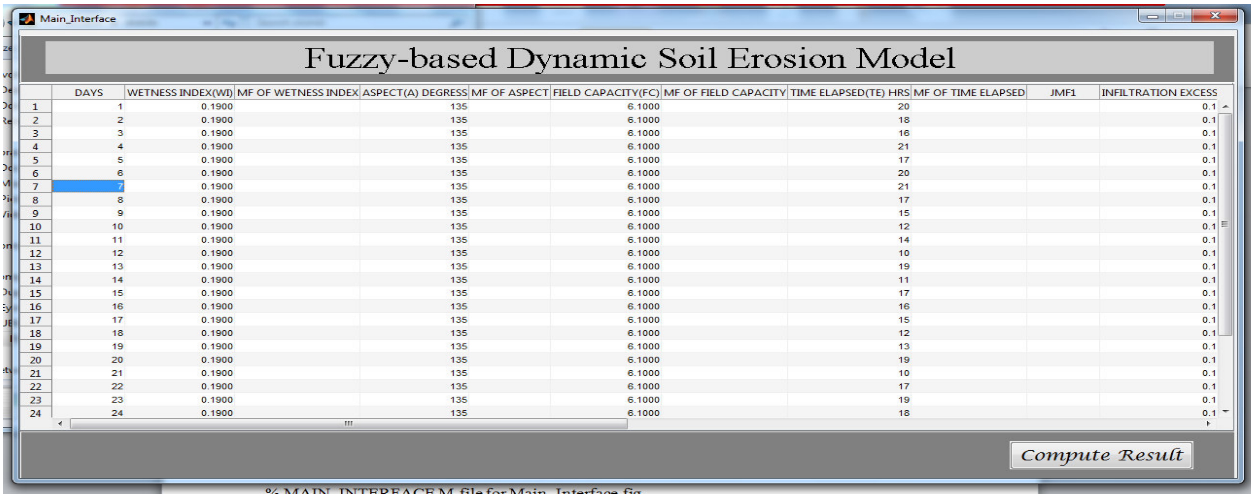
Table 2: Fudsem Data

Days	Wetness Index (m)	Aspect (Deg)	Field Capacity (m^3/m^3)	Time Elapsed (Hr)	Infiltration Excess (mm/Hr)	Rain Depth (mm)	Ndvi	Acc	Slope	K Index
1	0.19	135	6.1000	20	0.1598	0.75	0.25	10	0.05	0.0835
2	0.19	135	6.1000	18	0.1467	0.72	0.25	10	0.05	0.0835
3	0.19	135	6.1000	16	0.1457	0.65	0.25	10	0.05	0.0835
4	0.19	135	6.1000	21	0.142	0.64	0.25	10	0.05	0.0835
5	0.19	135	6.1000	17	0.156	0.64	0.25	10	0.05	0.0835
6	0.19	135	6.1000	20	0.153	0.6	0.25	10	0.05	0.0835
7	0.19	135	6.1000	21	0.157	0.56	0.25	10	0.05	0.0835
8	0.19	135	6.1000	17	0.156	0.75	0.25	10	0.05	0.0835
9	0.19	135	6.1000	15	0.157	0.65	0.25	10	0.05	0.0835
10	0.19	135	6.1000	12	0.159	0.56	0.25	10	0.05	0.0835
11	0.19	135	6.1000	14	0.158	0.64	0.25	10	0.05	0.0835
12	0.19	135	6.1000	10	0.143	0.75	0.25	10	0.05	0.0835
13	0.19	135	6.1000	19	0.145	0.64	0.25	10	0.05	0.0835
14	0.19	135	6.1000	11	0.156	0.63	0.25	10	0.05	0.0835
15	0.19	135	6.1000	17	0.159	0.56	0.25	10	0.05	0.0835
16	0.19	135	6.1000	16	0.153	0.6	0.25	10	0.05	0.0835
17	0.19	135	6.1000	15	0.156	0.56	0.25	10	0.05	0.0835
18	0.19	135	6.1000	12	0.157	0.66	0.25	10	0.05	0.0835
19	0.19	135	6.1000	13	0.158	0.73	0.25	10	0.05	0.0835
20	0.19	135	6.1000	19	0.156	0.72	0.25	10	0.05	0.0835
21	0.19	135	6.1000	10	0.158	0.73	0.25	10	0.05	0.0835
22	0.19	135	6.1000	17	0.154	0.64	0.25	10	0.05	0.0835
23	0.19	135	6.1000	19	0.153	0.63	0.25	10	0.05	0.0835
24	0.19	135	6.1000	18	0.154	0.62	0.25	10	0.05	0.0835
25	0.19	135	6.1000	16	0.154	0.65	0.25	10	0.05	0.0835
26	0.19	135	6.1000	13	0.156	0.63	0.25	10	0.05	0.0835
27	0.19	135	6.1000	15	0.157	0.56	0.25	10	0.05	0.0835
28	0.19	135	6.1000	14	0.143	0.55	0.25	10	0.05	0.0835
29	0.19	135	6.1000	12	0.156	0.65	0.25	10	0.05	0.0835
30	0.19	135	6.1000	13	0.146	0.64	0.25	10	0.05	0.0835

Table 3: Output of Fudsem Data

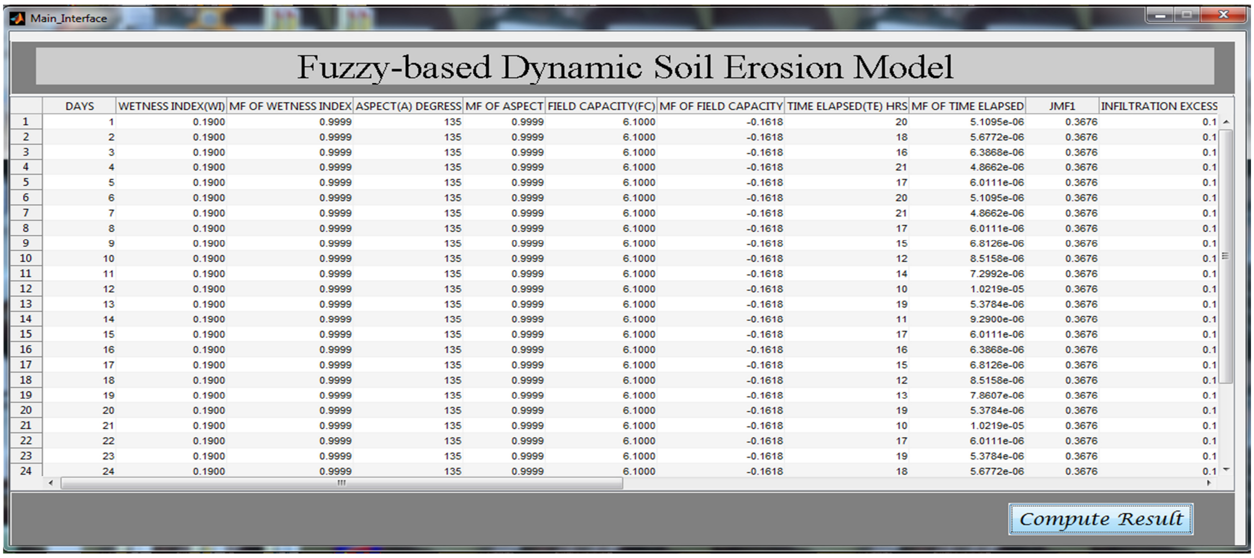
Days	JMF 1	JMF 2	JMF 3	JMF 4 (Final output)
1	0.3676	0.7680	0.5720	0.3851
2	0.3676	0.7680	0.5720	0.3851
3	0.3676	0.7680	0.5720	0.3851
4	0.3676	0.7680	0.5720	0.3851
5	0.3676	0.7680	0.5720	0.3851
6	0.3676	0.7680	0.5720	0.3851
7	0.3676	0.7680	0.5720	0.3851
8	0.3676	0.7680	0.5720	0.3851
9	0.3676	0.7680	0.5720	0.3851
10	0.3676	0.7680	0.5720	0.3851
11	0.3676	0.7680	0.5720	0.3851
12	0.3676	0.7680	0.5720	0.3851
13	0.3676	0.7680	0.5720	0.3851
14	0.3676	0.7680	0.5720	0.3851
15	0.3676	0.7680	0.5720	0.3851
16	0.3676	0.7680	0.5720	0.3851
17	0.3676	0.7680	0.5720	0.3851
18	0.3676	0.7680	0.5720	0.3851
19	0.3676	0.7680	0.5720	0.3851
20	0.3676	0.7680	0.5720	0.3851
21	0.3676	0.7680	0.5720	0.3851
22	0.3676	0.7680	0.5720	0.3851
23	0.3676	0.7680	0.5720	0.3851
24	0.3676	0.7680	0.5720	0.3851
25	0.3676	0.7680	0.5720	0.3851
26	0.3676	0.7680	0.5720	0.3851
27	0.3676	0.7680	0.5720	0.3851
28	0.3676	0.7680	0.5720	0.3851
29	0.3676	0.7680	0.5720	0.3851
30	0.3676	0.7680	0.5720	0.3851

The FuDSEM models divides its erosion prediction process into four subroutines and they are soil moisture potential (JMF1), runoff potential (JMF2), transport capacity potential (JMF3) and finally soil erosion potential (JMF4) which is actually the destination point. Each of these subroutines has some parameters that are linked together to estimate a particular a subroutine, which can also be called sub-subroutines. For instance, the soil moisture potential has the following parameters linked together to estimate it: time elapsed from previous rainfall (Te), wetness index (WI), hillslope aspect (SA), and field capacity. The membership functions of the data of these parameters are calculated using the formula given in (Figure 3a: Interface Showing User inputs) depending on the parameter being calculated since the raw data cannot be used directly in this model, they are integrated together into joint membership functions (JMFs), that is the membership function of the subroutine as a whole. The same process was carried out for 30 days with the total number of parameters used was ten. And the final output was the JMF4 (soil erosion potential) which is described to be between the ranges of 0 and 1 i.e. 0 for low potential and 1 for high potential, gave an output with the value 0.3851 implying that over a period of 30 days, the estimated area had low soil erosion potential. The model data was computed using MATLAB. Matlab is a high performance language for technical computing. It integrates computation, visualization, and programming in an easy to use environment where problems and solutions are expressed in familiar mathematical notation (Figure 3b: Interface Showing User outputs).



	DAYS	WETNESS INDEX(WI)	MF OF WETNESS INDEX	ASPECT(A) DEGRESS	MF OF ASPECT	FIELD CAPACITY(FC)	MF OF FIELD CAPACITY	TIME ELAPSED(TE) HRS	MF OF TIME ELAPSED	JMF1	INFILTRATION EXCESS
1	1	0.1900		135		6.1000		20			0.1
2	2	0.1900		135		6.1000		18			0.1
3	3	0.1900		135		6.1000		16			0.1
4	4	0.1900		135		6.1000		21			0.1
5	5	0.1900		135		6.1000		17			0.1
6	6	0.1900		135		6.1000		20			0.1
7	7	0.1900		135		6.1000		21			0.1
8	8	0.1900		135		6.1000		17			0.1
9	9	0.1900		135		6.1000		15			0.1
10	10	0.1900		135		6.1000		12			0.1
11	11	0.1900		135		6.1000		14			0.1
12	12	0.1900		135		6.1000		10			0.1
13	13	0.1900		135		6.1000		19			0.1
14	14	0.1900		135		6.1000		11			0.1
15	15	0.1900		135		6.1000		17			0.1
16	16	0.1900		135		6.1000		16			0.1
17	17	0.1900		135		6.1000		15			0.1
18	18	0.1900		135		6.1000		12			0.1
19	19	0.1900		135		6.1000		13			0.1
20	20	0.1900		135		6.1000		19			0.1
21	21	0.1900		135		6.1000		10			0.1
22	22	0.1900		135		6.1000		17			0.1
23	23	0.1900		135		6.1000		19			0.1
24	24	0.1900		135		6.1000		18			0.1

Figure 3a: Interface Showing User Inputs



	DAYS	WETNESS INDEX(WI)	MF OF WETNESS INDEX	ASPECT(A) DEGRESS	MF OF ASPECT	FIELD CAPACITY(FC)	MF OF FIELD CAPACITY	TIME ELAPSED(TE) HRS	MF OF TIME ELAPSED	JMF1	INFILTRATION EXCESS
1	1	0.1900	0.9999	135	0.9999	6.1000	-0.1618	20	5.1095e-06	0.3676	0.1
2	2	0.1900	0.9999	135	0.9999	6.1000	-0.1618	18	5.6772e-06	0.3676	0.1
3	3	0.1900	0.9999	135	0.9999	6.1000	-0.1618	16	6.3868e-06	0.3676	0.1
4	4	0.1900	0.9999	135	0.9999	6.1000	-0.1618	21	4.8662e-06	0.3676	0.1
5	5	0.1900	0.9999	135	0.9999	6.1000	-0.1618	17	6.0111e-06	0.3676	0.1
6	6	0.1900	0.9999	135	0.9999	6.1000	-0.1618	20	5.1095e-06	0.3676	0.1
7	7	0.1900	0.9999	135	0.9999	6.1000	-0.1618	21	4.8662e-06	0.3676	0.1
8	8	0.1900	0.9999	135	0.9999	6.1000	-0.1618	17	6.0111e-06	0.3676	0.1
9	9	0.1900	0.9999	135	0.9999	6.1000	-0.1618	15	6.8126e-06	0.3676	0.1
10	10	0.1900	0.9999	135	0.9999	6.1000	-0.1618	12	8.5158e-06	0.3676	0.1
11	11	0.1900	0.9999	135	0.9999	6.1000	-0.1618	14	7.2992e-06	0.3676	0.1
12	12	0.1900	0.9999	135	0.9999	6.1000	-0.1618	10	1.0219e-05	0.3676	0.1
13	13	0.1900	0.9999	135	0.9999	6.1000	-0.1618	19	5.3784e-06	0.3676	0.1
14	14	0.1900	0.9999	135	0.9999	6.1000	-0.1618	11	9.2900e-06	0.3676	0.1
15	15	0.1900	0.9999	135	0.9999	6.1000	-0.1618	17	6.0111e-06	0.3676	0.1
16	16	0.1900	0.9999	135	0.9999	6.1000	-0.1618	16	6.3868e-06	0.3676	0.1
17	17	0.1900	0.9999	135	0.9999	6.1000	-0.1618	15	6.8126e-06	0.3676	0.1
18	18	0.1900	0.9999	135	0.9999	6.1000	-0.1618	12	8.5158e-06	0.3676	0.1
19	19	0.1900	0.9999	135	0.9999	6.1000	-0.1618	13	7.8607e-06	0.3676	0.1
20	20	0.1900	0.9999	135	0.9999	6.1000	-0.1618	19	5.3784e-06	0.3676	0.1
21	21	0.1900	0.9999	135	0.9999	6.1000	-0.1618	10	1.0219e-05	0.3676	0.1
22	22	0.1900	0.9999	135	0.9999	6.1000	-0.1618	17	6.0111e-06	0.3676	0.1
23	23	0.1900	0.9999	135	0.9999	6.1000	-0.1618	19	5.3784e-06	0.3676	0.1
24	24	0.1900	0.9999	135	0.9999	6.1000	-0.1618	18	5.6772e-06	0.3676	0.1

Figure 3b: Interface Showing User Outputs

CONCLUSION

This study was done using properties of fuzzy models to predict soil degradation, precisely soil erosion. From the work, FuDSEM was better defined than other ordinary models and it's simpler to use due to its definition. Also, it is incapable of generalizing as it only answers what is written in the rule base. It is not robust in the relation to topological changes of the system as such changes would demand operations in the rule base. This model is therefore recommended to be used in the agricultural sector of the economy to predict lands that are prone to degradation as it will help to adequately monitor the rate of degradation in soil after cultivation so that adequate measures can be taken to guide against it.

REFERENCE

Admin (2009). Blog of IECYCLE accessed 23rd March, 2014.

Ahamed, T.R.N., Rao, K.G., Murthy, J.S.R., (2000). *Fuzzy Class Membership Approach to Soil Erosion Modeling*. Agric. Syst. 63, 97-110.

Bosworth, D.A., Foster, A.B. (1972). *Approved Practices in Soil Conservation.* The Interstate Printers and Publishers.

Burrough, P.A., Macmillan, R.A., Vandeursen, W., (1992). Fuzzy Classification Methods for Determining Land Suitability from Soil Profile Observations and Topography. *Journal of Soil Science* 43, 193-210.

Coulthard, T.J., Macklin, M.G., Kirkby, M.J., (2002). A Cellular Model of Holecene Upland River Basin and Alluvial Fan Evolution. *Earth Surf. Proc. Land.* 27, 269-288

DeJong, S.M., Parrachini, M.L., Bertolo, F., Folving, S., Megier, J., DeRoo, A.P.J., (1999). Regional Assessment of Soil Erosion Using the Distributed Model SEMMED and Remotely Sensed Data. *Catena* 37, 291-308

DeRoo, A.P.J., (1998). Modeling Runoff and Sediment Transport in Catchments Using GIS. *Hydrol. Process*. 12, 905-922.

DeRoo, A.P.J., Wesseling, C.G., Ritsema, C.J., (1996). LISEM: A Single-Event Physically Based Hydrological And Soil Erosion Model For Drainage Catchment. *Theory, Input and Output*. *Hydrol. Process.* 10, 1107-1117.

Figueiredo, M., and Gomide, F. (1999). Design of Fuzzy Systems Using Neuro-Fuzzy Networks. *IEEE Transactions on Neural Networks, 10*(4), 815-827.

Folly, A., Quinton, J.N., Smith, R.E., (1999). Evaluation of the EUROSEM Model Using Data from the Catsope Watershed, the Netherlands. *Catena* 37, 507-519.

Jang, R. (1992). Neuro-Fuzzy Modeling: Architectures, Analysis and Applications. Berkley: PhD Thesis, University of California.

Jetten, V., DeRoo, A., Favis-Mortlock, D., (1999). Evaluation of Field Scale and Catchment-Scale Erosion Models. *Catena* 37, 521-541.

Jetten, V., Govers, G., Hessel, R., (2003). Erosion Models: Quality of Spatial predictions. Hydrol. Process. 17, 887-900.

Juang, F.C., and Chinlin, T. (1998). An Online Self-constructing Neural Fuzzy Inference Network and its Applications. *IEEE Transactions on Fuzzy Systems* (pp. 12-32).

Kasabov Qunsong N. (1999). Dynamic Evolving Fuzzy Neural Networks with 'in-out-of-n' Activation Nodes for On-line Adaptive Systems. *Technical Report TR99/04, Department of Information Science,* University of Otago.

Kirkby, M.J., McMahon, M.L., (1999). MEDRUSH And Catsope Catchment- The Lessons Learned. *Catena* 37, 495-506.

Kosko B. (1992). Neural Networks and Fuzzy Systems: A dynamical System Approach to Machine Intelligence. New Jersey: Prentice Hall, Eaglewood Cliffs.

Lin, T.C., Lee, C.S. (1991). Neural Network Based Fuzzy Logic Control and Decision System. *IEEE Transactions on Computers, 40*(12), 1320-1336.

Merritt, W.S., Letcher, R.A., Jakeman, A.J., (2003). A Review of Erosion and Sediment Transport Models. Environmental Modeling Software 18, 761-799.

Metternicht, G., (2001). Assessing Temporal and Spatial Changes of Salinity Using Fuzzy Logic, Remote Sensing and GIS, Foundations of an Expert System. *Ecology Modeling* 144, 163-179.

Mitasova, H. 1996. GIS tools for erosion/deposition modeling and Multidimensional Visualization. Part III: process-based Erosion Simulation, Geographic Modeling and System Laboratory. University of Illinois: Illinois.

Mitra, B., Scott, H.D., Dixon, J.C., McKimmey, J.M., (1998). Applications of Fuzzy Logic to the Prediction of Soil Erosion in a Large Watershed. Geoderma 86, 183-209.

Morgan, R.P.C., Quinton, J.N., Rickson, R.J., (1992). EUROSEM Documentation Manual. Version 1, June 1992. Silsoe College, Silsoe.

Nauck D. (1995). Beyond Neuro-Fuzzy Systems: Perspectives and Directions. *Proc. Of the Third European Congress on Intelligent Techniques and Soft Computing (EUFIT'95).* Aachen.

Nauck, D., Klawon, F., Kurse R. (1997). *Foundations of Neuro-Fuzzy Systems*. J wiley and Sons.

Nauck, D., Kurse, R. (1997). Neuro-Fuzzy Systems for Function Approximation. *Fourth International Workshop on Fuzzy-Neuro Systems.*

Nearing, M.A., Foster, G.R., Lane, L.J., Fikner, S.G., (1989). A Process Based Soil Erosion Model for USDA-Water Erosion Prediction Project Technology. *Trans. Am. Soc. Agric. Eng.* 32, 1587-1593.

Pedreyz and Gomide, FSE. (2007). *Fuzzy System Engineering towards Human-centric Computing.*

Sagy Cohen, Tal Svoray, Jonathan B. Lahonne, Yulia Alexandrov. (2008). *Journal of Hydrology, 356*(1 2), 185-198.

Schmidt, J., Von Werner, M., Micheal, A., (1999). Application of the Erosion 3D Model to the Catsope Watershed, the Netherlands. *Catena* 37, 449-456.

Schorl, J.M., Sonneveld, M.P.W., Veldkamp, A., (2000). Three Dimensional Landscape Processing Modeling: The Effects of DEM Resolution*. Earth Surf. Proc. Land.* 25, 1025-1034.

Sulzberger, S., Tschichold, N., Vestli, S. (1993) FUN: Optimization of Fuzzy Rule Based Systems Using Neural Networks. *Proceedings of IEEE conference on Neural Networks* (pp. 312-316). San Francisco

Svoray, T., Mazor, S., Bar, P., (2007). How is Shrub Cover Related to Soil Moisture and Patch Geometry in the Fragmented Landscape of The Northern Negev Desert? *Landscape Ecology* 22, 105-116.

Tano, S., Oyama, T., Arnould T. (1996). Deep Combination of Fuzzy Inference and Neural Network Fuzzy Inference. *Fuzzy Sets and Systems, 82*(2), 151-160.

Tayfur, G., Ozdemir, S., Singh, V.P., (2003). Fuzzy Logic Algorithm for Runoff Induced Sediment Transport from Bare Soil Surfaces. *Advanced Water Resources* 26, 1241-1256.

Tayfur, G., Singh, V.P., (2006). ANN and Fuzzy Logic Models for simulating event Based Rainfall Runoff. *Journal of Hydrology. Eng.,* ASCE 132, 1321-1329.

Trimble, S.W., Crosson, P., (2000). Measurements and Models of Soil Loss Rates-Response. Science 290, 1301.

Tucker, G.E., Lancaster, S.T., Gasparini, N., Bras, M.R.L., Rybarczyk, S.M., (2001). An Object Oriented Framework For Distributed Hydrology And Geomorphic Modeling Using Triangulated Irregular Networks. *Comput. Geosci.* UK 27, 959-973.

Tucker, G.E., Slingerland, R.L., (1994). Erosional Dynamics, Flexural Isostasy, And Long-Lived Escarpments-A Numerical Modelling Study. *J. Geophys. Res. Solid Earth* 99, 12229-12243.

Van Rompaey, A.J.J., Verstraeten, G., Van Oost, K., Govers, G., Poesen, J., (2001). Modeling Mean Annual Sediment Yield Using a Distributed Approach. *Earth Surf. Proc. Land.* 26, 1221-1236.

Willgoose, G.R., Bras, R.L., Rodriguez-Iturbe, I., (1991). Results from a New Model of River Basin Evolution. *Earth Surf. Proc*. 16, 237-254.

Yitayew, M., Pokrzywka, S.J., Renard, K.G. 1999. "Using GIS for facilitating erosion estimation." Journal of Applied Engineering in Agriculture.

Zadeh, L.A. (1965).*Fuzzy Sets Information and Control,* 8, 338-353.

Zhu, A.X., Band, L.E., Dutton B., Nimlos, T.J., (1996). *Automated Soil Inference Under Fuzzy Logic. Ecological Modeling*. 90, 123-145.