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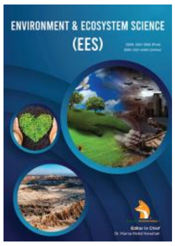

RESEARCH ARTICLE

AN ASSESSMENT AND PREDICTION OF SOIL EROSION RISK USING MODIFIED FOURNIER INDEX AND MACHINE LEARNING ALGORITHM: AN EXTERNAL AGRICULTURAL PROJECT RISK

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ABSTRACT

Soil erosion, defined as a naturally occurring process that adversely affect all landform leads to increased pollution and sedimentation in rivers and streams which causes decline in fish and other forms of aquatic life. Suitable land use guided by scientific research findings can help reduce these impacts. The current study therefore aimed at characterisation and prediction of soil erosion by water using Modified Fournier Index methodology. Prior to final data analysis, data quality checks were deployed where outliers were detected, removed and replace by expectation maximum algorithm aided by SPSS. A machine learning algorithm, Neural Network was applied to forecast probable annual values of the Modified Fournier Index (Cp). Major findings exhibited a significant decreasing trend implying a high likelihood of drought events in the area. This phenomenon provides an insight for possible shift in the type of soil erosion risk to prevail in the near future, where soil particles will be prone to wind erosion. The Neural Network forecasted Fournier index values were seen diminishing annually. From these results it is therefore recommended that more studies be undertaken on drought risk analysis since Fournier index values are diminishing giving way to drought events. This information will provide details necessary for informed decision in the protection and sustainability of the Agricultural activities in the study area.

KEYWORDS

Soil erosion risk, Fournier index, Machine learning algorithm, Neural Network, Southern Lesotho

1. INTRODUCTION

Soil erosion is a progressive process that happens as water or wind detaches and extracts soil particles, allowing the soil to deteriorate. Soil degradation and poor water quality as a result of deforestation and surface runoff have become major concerns all over the world (Andrello, Appoloni, Cassol, and Melquiades, 2006). The problem can escalate to the point that the land can no longer be cultivated and must be abandoned (Borselli and Torri, 2007). Many agricultural civilizations have collapsed as a result of inadequate land and natural resource management, and the past of such civilizations serves sas a strong reminder to conserve our natural resources (Mossaad and Wu, 1984). Erosion is a major issue for fertile agricultural land as well as water quality issues (Andrello et al., 2006). Controlling sediment must be an important part of every soil management method in order to enhance water and soil quality (Igwe, 2017). Eroded topsoil may be carried by wind or water through streams and other waterways. Sediment is a by-product of land erosion that results mainly from sheet and rill erosion in upland areas and, to a lesser extent, from cyclic erosion activity in gullies and drainage ways. Soil erosion has a major impact on water quality, particularly when soil surface runoff occurs. The development of sediment and the erosion of soil are inextricably connected (Mosbahi, Benabdallah, and Boussema, 2013). As a result, stabilizing the sediment source by managing erosion is the most effective way to reduce sediment production. To control erosion, a variety of management methods can be used, but first you must understand the factors that cause soil erosion. Soil erosion is the detachment and displacement of soil particles from their original location caused by water or wind activity. Consequently, the key purpose of erosion management is to reduce the effects of water or wind forces (Ekholm and Lehtoranta, 2012). In agricultural development projects, water erosion is the most severe erosion problem (Rose et al., 2007). When a bare-sloped soil surface is exposed to rainfall, the rainfall level exceeds the rate of soil intake, or infiltration rate, resulting in soil-surface runoff. Soil erosion occurs in two stages: 1) detachment of soil particles caused by raindrop damage, splash, or flowing water; and 2) transport of detached particles caused by splash or flowing water. Consequently, soil erosion is a physical mechanism that necessitates energy, and its management necessitates the introduction of complex measures to dissipate this energy (Retallack, 2005).

1.2 Description of the Study Area

Lesotho is a small, mountainous, landlocked country bordered by South Africa, a much larger neighbour. It has a population of around two million people and a nominal GDP per capita of $1,299 (Shale and Rantšo, 2019). Land degradation caused by soil erosion has been described as one of Lesotho's most serious environmental challenges (Molapo, 2016). Soil erosion has left the landscape scarred with deep gullies and dongas, and the soil has been deposited as sediment in lakes and rivers, diminishing the aesthetic appearance of water bodies with heavy sediment loads (Kapa

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and Shale, 2014). Soil erosion and hence land loss are largely the product of inadequate land management practices, the most egregious of which is the mismanagement of rangelands due to overgrazing (McConkey et al., 2000). Addressing the issue of overgrazing in rangelands is one of the country's top priorities, particularly given that livestock production provides a living for many people in rural Lesotho and livestock products such as wool and mohair contribute significantly to the country's GDP. On the one side, the wool and mohair industries depend heavily on well-managed and stable rangelands. Rangelands management, on the other hand, is considered to be one of the most critical aspects of tackling land loss and contributing to ecosystem resilience (Molapo, 2016). Figure 1 below shows the map of Lesotho and the Southern part that the study focussed on, segmented by line AB.

Latitude	Longitude
Bottom left=-30.675	Bottom left=27.1060
Upper-right = -29.735	Upper-right = 29.0643

Figure 1: Lesotho Map, Source: (Kapa and Shale, 2014)

2. Methods and Materials

The modified Fournier index is defined by the equation below;

$$Cp = \frac{P^{\wedge}2Max}{P} \quad (1)$$

where:

Cp is the Fournier index,

P is the total annual/seasonal rainfall (mm), and

Pmax is the rainfall amount in the wettest month/season.

Table 3.1 depicts rainfall erosion risk groups based on the Fournier index (Cp). Several factors, however, contribute to the possibility of soil erosion. In a universal soil loss erosion (USLE) equation, these are included as follows:

$$A = R.K.L.S.C.P \quad (2)$$

Where:

A is the average annual soil loss (Mg $ha^{-1} yr^{-1}$),

R is the rainfall erosivity index,

K is the soil erodibility factor,

L is the slope length factor,

S is the slope gradient factor,

C is the vegetation protection cover and

P is the conservation protection factor.

Table 1 shows the classification of rainfall erosion risk based on the Fournier index (Cp), risk classes and the estimated amount of soil in hectares likely to be lost.

Table 1: Classes of rainfall erosion risk based on the Fournier index (Cp)

Class No	Erosion Risk Class	Fournier Index (C_p)	Soil Loss (T/ha year)
1	Very Low	<20	<5
2	Low	21-40	5-12
3	Moderate	41-60	12-50
4	Severe	61-80	50-100
5	Very Severe	81-100	100-200
6	Extremely Severe	>100	>200

Source: (Andrello et al., 2006)

2.1 Neural networks

A neural network is a network or circuit of neurons, or in today's words, an artificial neural network made up of artificial neurons or nodes (Haworth and Velliste, 2018). Thus, a neural network can be either a biological neural network (made up of real biological neurons) or an artificial neural network (made up of artificial biological neurons) for solving artificial intelligence (AI) problems (Bengio et al, 2005). The biological neuron's interactions are represented as weights. An excitatory relation is defined by a positive weight, while inhibitory connections are represented by a negative weight. A weight is applied to all inputs before they are summed. These artificial networks could be used for predictive modelling, adaptive control, and other applications that require a dataset to train (El-Bakry and Zhao, 2005). Self-learning based on experience may take place inside networks, which can draw conclusions from a large and apparently unrelated collection of data (Barra et al., 2012). The Zaitun computer program was used in this research to predict and model the risk of soil erosion in the study area. Figure 2 shows a simple neural network diagram.

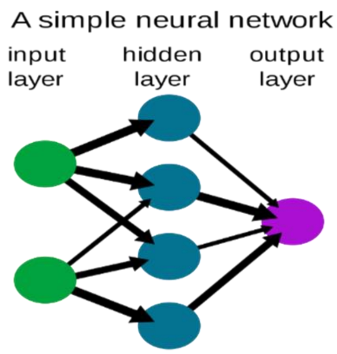

Figure 2: A simple neural network diagram

Source: (Haworth and Velliste, 2018)

3. Results and Discussion

Figures 2 and 3 show the visualisation of the input dataset, precipitation from 1981 to 2019 of the study area. This was done in order to assess the presence of any outliers in the dataset. From the figure 2, it can be seen that two distinct outliers were present. This was confirmed by a box and whisker plot in figure 2 which instead revealed three more and that the dataset is positively skewed. All the outliers were removed, and gaps replaced by expectation maximum algorithm aided by SPSS. Another important observation from figure 2 is that precipitation seems to be diminishing as time moves.

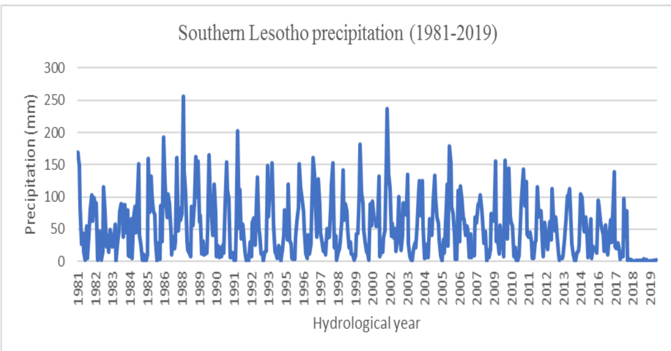

Figure 3: Southern Lesotho precipitation graph (1981-2019**)**

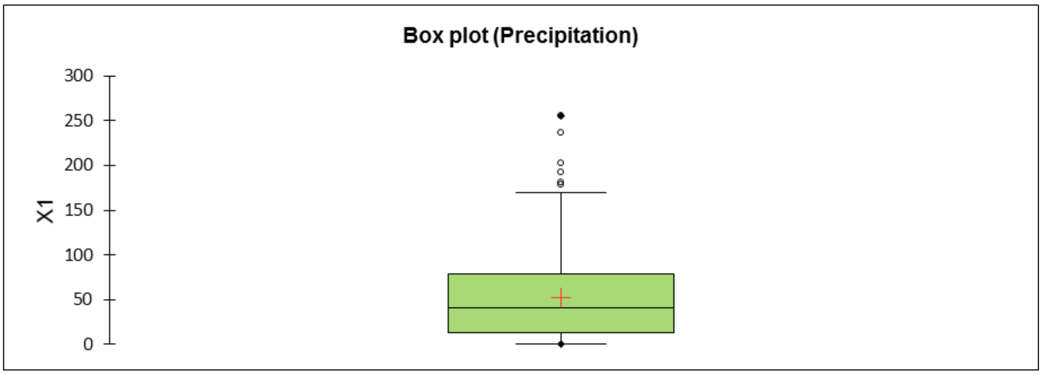

Figure 4: Southern Lesotho precipitation box and whisker plot (1981-2019)

Table 2 depicts the monthly precipitation descriptive statistics for the study area. This area receives an average precipitation of 51.9 mm with a minimum and maximum of 255.5 mm respectively. The variance is almost equal to the mean precipitation of this study area. Furthermore, seasonal time series was extracted from the monthly precipitation dataset to explore the behavioural patterns in order to inform decision making to mitigate risk effects of soil erosion. Figure 4 displays the seasonal graphs of precipitation in the study area. Modified Fournier indices for the assessment of rail fall soil erosion was computed on two temporal scales; seasonal and annual basis as depicted in table 3 showing descriptive analysis of these two scales.

Table 2: Southern Lesotho monthly precipitation descriptive statistics

Statistic	Precipitation
Nbr. of observations	468
Minimum	0.010
Maximum	255.520
1st Quartile	13.455
Median	40.485
3rd Quartile	78.423
Mean	51.994
Variance (n-1)	2127.585
Standard deviation (n-1)	46.126

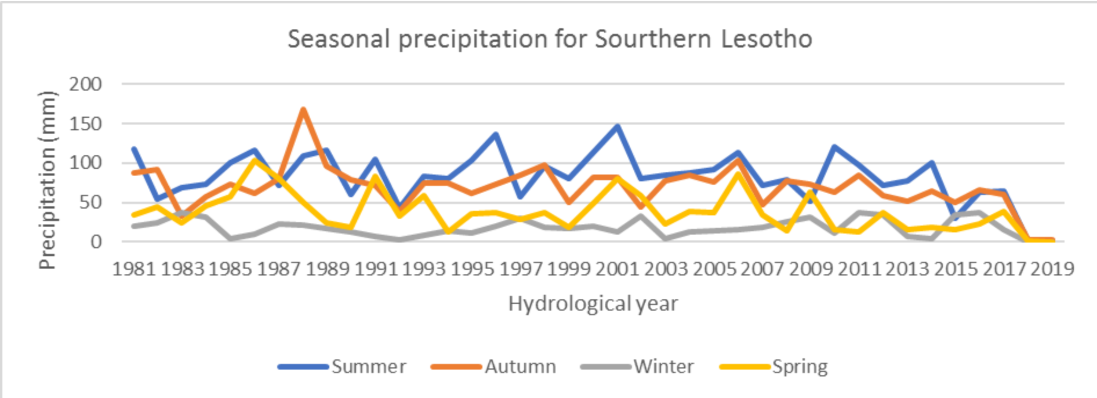

Figure 5: Southern Lesotho seasonal precipitation graph (1981-2019)

Table 3: Southern Lesotho seasonal and annual Fournier index precipitation descriptive statistics

Variable	Obs. without missing data	Minimum	Maximum	Mean	Std. deviation
Summer	39	1.347	145.800	82.475	31.795
Autumn	39	2.847	167.667	69.425	27.335
Winter	39	0.357	37.327	17.972	10.967
Spring	39	0.117	103.073	38.105	24.396
Cp_Annual	39	0.780	62.803	28.482	13.480

The computed Modified Fournier index time series was correlated with all seasons and annual Fournier index time series by a non-parametric correlation test, (Spearmans) as shown in table 4. The correlation test revealed a positively strong correlations between Fournier indices and Summer, Autumn and Spring precipitations. Only the winter precipitation had a non-significant negative influence on the computed annual Modified Fournier indices (Cp). Of the three strongly positive correlations, Summer seasons seem to carry the most variability with the correlation coefficient of 0.672. This is evident that soil erosion risks in the area are mostly contributed by Summer, Autumn and Spring season in acceding order. The Fournier indices time series was subjected to Mann Kendall trend test analysis as shown in figure 3. A significantly decreasing trend pattern with a coefficient of determination of a unit was observed. These results imply a decrease in soil erosion severity but indicate the beginning of drought events in the area, and as such the loss of soil maybe attributed to wind erosion instead, where soil particles are loose and susceptible to this type of soil erosion.

Table 4: Correlation matrix (Spearman): Seasons and annual Modified Fournier index (Cp)					
Variables	Summer	Autumn	Winter	Spring	Cp_Annual
Summer	**1**	**0.458**	-0.147	**0.357**	**0.672**
Autumn	**0.458**	**1**	0.184	0.293	**0.556**
Winter	-0.147	0.184	**1**	0.076	-0.135
Spring	**0.357**	0.293	0.076	**1**	**0.504**
Cp Annual	**0.672**	**0.556**	-0.135	**0.504**	**1**
Values in bold are different from 0 with a significance level alpha=0.05					

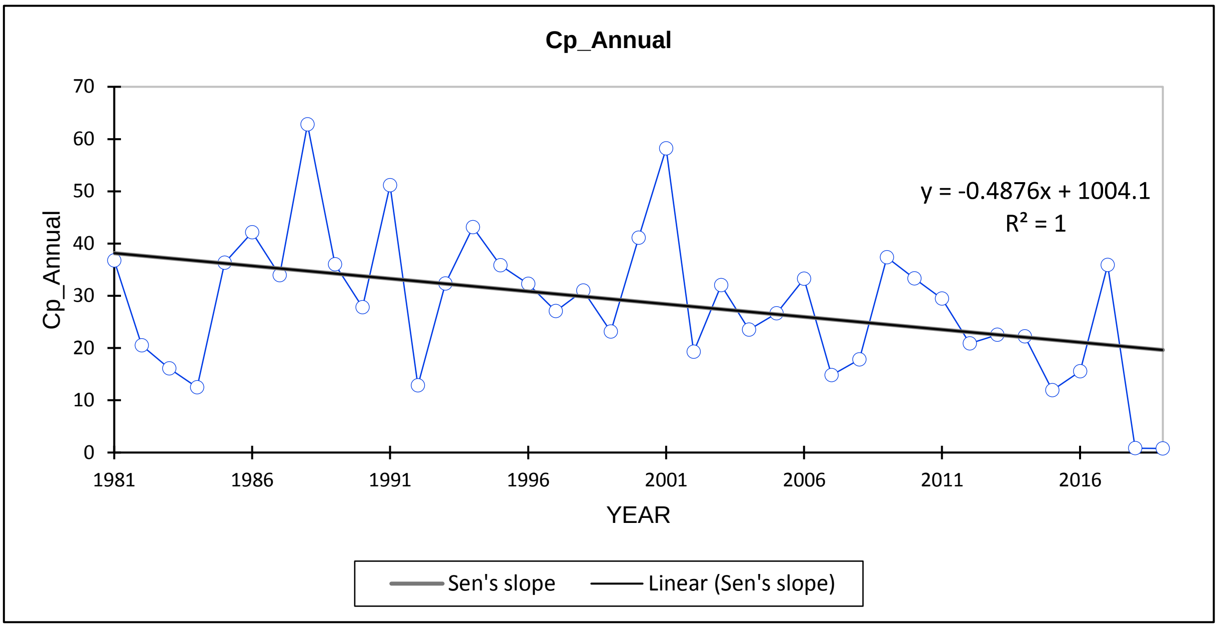

Figure 6: Southern Lesotho's Annual Fournier index (Cp) graph (1981-2019)

Table 5: Mann Kendall's trend test	
Kendall's tau	-0.298
S	-221.000
Var(S)	6833.667
p-value (Two-tailed)	0.008
alpha	0.05
An approximation has been used to compute the p-value.	

Post the analysis of the Fournier index trends and correlations, where Summers were observed to have the most influence followed by Autumns, a machine learning algorithm was applied to provide more accurate predictions given the determined decreasing trend of the Fournier index time series. Table 6 and 7 display the Modified Fournier Index classification interpretations and Neural network structure of the model respectively. Table 7 depicts the model structure where 15 input layer, 12 hidden layer and 1 output layer neurons were used in the training and prediction of the Fournier index values. This model resulted in low Mean square error of 0.03554. Table 8 shows forecasted Fournier index values using the Neural Network algorithm for the next four years from 2020 to 2023.

Table 6: Modified Fournier index classification

Class No	Erosion Risk Class	Fournier Index (C_p)	Soil Loss (T/ha year)
1	Very Low	<20	<5
2	Low	21-40	5-12
3	Moderate	41-60	12-50
4	Severe	61-80	50-100
5	Very Severe	81-100	100-200
6	Extremely Severe	>100	>200

Source: (Mosbahi et al., 2013)

Table 7: Neural Network structure model summary	
Variable/parameter	**Modified Fournier index**
Included Observation	24 (After Adjusting Endpoints)
Network Archiecture	
Input Layer Neurons	15
Hidden Layer Neurons	12
Output Layer Neurons	1
Activation Function	**Bipolar Sigmoid Function**
Back Propagation Learning	
Learning Rate	0.05
Momentum	0.5
Criteria	
Error	0.000366
MSE	0.035954
MAE	0.084075

Table 8: Neural Network Forecasted Cp	
Year	Forecasted
2020	24.4298
2021	8.5309
2022	0.3825
2023	1.7838

4. Conclusion and Discussion

In conclusion, soil erosion is one of those risks that adversely impact agricultural production hence the need for assessment to aid informed decision making. The study area has exhibited a significant decreasing trend implying a high likelihood of drought events in the area. This phenomenon provides an insight for possible shift in the type of soil erosion risk to prevail in the near future, where soil particles will be prone to wind erosion. The Neural Network forecasted Fournier index values were seen diminishing annually as depicted in table 7. From these results it is therefore recommended that more studies be undertaken on drought risk analysis since Fournier index values are diminishing giving way to drought events. This information will provide details necessary for informed decision in the protection and sustainability of the Agricultural activities in the study area.

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