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Abstract: *Land use/land cover (LULC) change, particularly urbanization has been significantly increasing due to the exponential population growth and has substantially altered the environment. It has been established that LULC is an important element of erosion and sedimentation. In this study, the Revised Universal Soil Loss Equation (RUSLE) model was used to determine the potential soil loss in changing LULC in Porac River Basin in Pampanga. Future LULC was developed using the Modules for Land Use Change Simulations (MOLUSCE), incorporating Cellular Automata–Artificial Neural Network (CA–ANN) method in predicting transitions. LULC simulation has resulted in a kappa statistics value of 0.566 denoting moderate agreement. Results show an increase of 202.91% in built-up areas, an increase of 52.41% in forest areas, and a decrease of 48.34% in cropland. A slight increase of average annual soil loss from 15.10 t ha^{-1}yr^{-1}, to 15.46 t ha^{-1}yr^{-1}in 2010 to 2030 has been seen. This study shows how land cover develops over time and how it affects the sediment dynamics in a river basin.*

Keywords: cellular automata artificial neural network (CA–ANN)**;** land use/land cover (LULC); modules for land use change simulations (MOLUSCE); revised universal soil loss equation (RUSLE); soil loss.

1. INTRODUCTION

Over the past few decades, urbanization has been evidently increasing due to the exponential demand of growing population for more housing and socio-economic infrastructures. This demand has been mainly expressed in terms of impermeable expansion altering the natural environment and putting more concrete land cover. Aside from the increasing rainfall volume attributed to climate change, the changes in Land use/land cover (LULC) particularly expansion of impervious surfaces and human settlements has been reported to affect the interaction between surface and subsurface flow pathways. These changes reduce infiltration [1] and lead to stormwater runoff peaks that are higher in magnitude and shorter in duration [2] subsequently affects the sediment dynamics [3]. Correlation analysis has shown significant evidence of a strong positive relationship between runoff and sedimentation [4].

Erosion and sedimentation caused by raindrops and water flow involve three main processes: soil detachment, transport and deposition. The rate of erosion within a catchment is influenced by a combination of physical factors and management variables. While its precise measurement would not be feasible, soil loss equations have been developed to extrapolate limited erosion data across various condition and location. The most used soil loss equation is the Revised Universal Soil Loss Equation (RUSLE) [5] which is designed to predict long-term annual average of soil loss in a watershed. It is an enhanced version of USLE, a five-factor model that estimates the anticipated rate of soil erosion based mainly on terrain, land use and land cover (LULC) and rainfall. Its extensive application in various watershed globally has established the validity of its effectiveness for predicting rainfall-induced erosion. In the Philippines, its integration with Geographic Information System (GIS) for soil loss modelling has been conducted in Cagayan [6], Marinduque [7], Bukidnon [8], Aklan [9], and Nueva Ecija [10]. However, significant gaps still remain in data availability and accessibility including up-to-date LULC conditions.

The change in LULC has become an essential tool in different field of studies due its significant correlation with the ecosystem. It has been established that the change in LULC has triggered the imbalances in hydrological and ecosystem processes [3]. Thus, it has to be thoroughly analyzed to understand more its effect on the characteristics of runoff and sedimentation variation [4]. To investigate the effect of LULC in the future, simulation models that would adopt probabilistic technique to project its future changes is essential [11]. The Modules for Land Use Change Simulations (MOLUSCE), a recently developed GIS-based tool, is considered one of the most effective models for projecting future LULC. It offers various functionalities, including the generation of a transition probability matrix through the Cellular Automata–Artificial Neural Network (CA–ANN) method. It also supports simulation-based modeling using logistic regression (LR), multi-criteria evaluation (MCE), artificial neural networks (ANN), and weights of evidence (WoE). In the final stage of the simulation process, the Cellular Automata (CA) model is utilized to estimate and predict future LULC patterns [11].

In this study, MOLUSCE will be used to predict the LULC of the Porac River Basin in Pampanga. LULC maps for the years 2010, 2020, and 2030 (projected) will serve as inputs to the RUSLE model for estimating and analyzing soil loss within the catchment. This study aims to assess the effect of urbanization and impervious expansion to soil loss. This would help us to clearly understand the importance of sustainable formulation of future land management plan and pollution control strategies.

2. METHODOLOGY

2.1 Study Site

The study site is the delineated Porac River Basin, which spans through Porac, Guagua, and Floridablanca in Pampanga, Philippines covering an area of 113.60 km^2. The river stretches for 30.5 km from the upstream to the outflow point, geographically located at 15.009°E, 120.533°N, which is a DPWH streamflow gauge (RO3.016) station point. The river basin locates the La Salle Botanical Gardens (LSBG), approximately 24 hectares, situated in the northern region of the catchment. It is a part of an estate development under Ayala Alviera which aims to serve as the area's greenbelt.

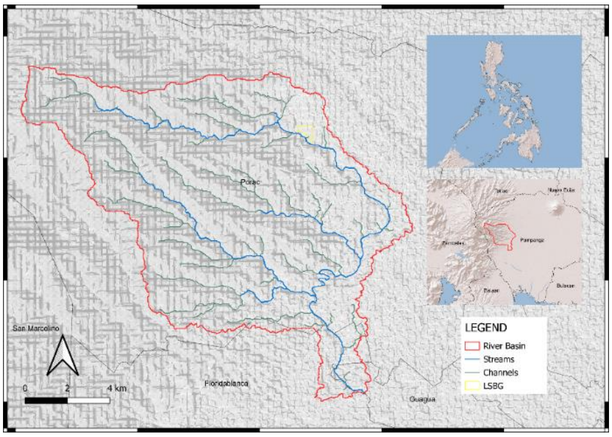

Fig. 1. Porac River Basin

2.2 MOLUSCE Land Use/Land Cover Prediction

MOLUSCE is a recently developed GIS tool that has become effective and widely used to predict future LULC scenarios [12]. It creates transition probability matrices based on the CA-ANN approach using various machine learning algorithms such as logistic regression, multi-criteria evaluation, ANN, and weights of evidence. It has been demonstrated that the combined application of machine learning and GIS has enabled rapid and cost-effective assessment of both the current and future conditions of LULC [13]. Several studies have analyzed how LULC transitions, modeled using the MOLUSCE, influence hydrological processes within a watershed [14-16].

2.2.1 Data Inputs

LULC data of the study area were gathered from NAMRIA-GeoPortal. The duration of the future LULC condition to be modeled is determined by the interval between the initial and final LULC inputs [17]. In this case, the five-year interval between 2010 (initial) and 2015 (final) will be used to predict 2020. Modeling LULC change requires spatial variables that will serve as change predictors. The variables presented in Table 7 were considered [18-19].

Table 1. Spatial Variables (Predictors) of LULC Change

Spatial Variables (Predictors)	Source
Digital Elevation Model (DEM)	USGS
Slope	USGS (from DEM)
Distance from roads	OpenStreetMap
Distance from rivers	Google Satellite
Distance from forest	Google Satellite
Distance from urban settlements	OpenStreetMap
Population density (per barangay)	Philippine Statistics Authority (PSA)

2.2.2 Transitional Potential Modeling and Cellular Automata (CA) Simulation

The MOLUSCE uses Cellular Automation (CA) model to simulate future scenarios, implying the probabilities of land use transition by Artificial Neural Network (ANN) learning process [20]. ANN is one of the machine learning algorithms that analyzes training data to identify underlying trends. ANN first determines the likelihood of transitioning one LULC to another [17]. These transition probabilities are then spatially allocated using the CA model, which considers the influence of neighboring cells to simulate realistic LULC dynamics. The simulated model will then be validated using the Kappa Statistics (KS) which weighs the agreement between the simulated and actual scenario. It is often used to assess classification accuracy [20-21]. The KS equation is shown below:

$$KS = (P_0 - P_e) / (1 - P_e) \qquad \text{(Eq. 1)}$$

Where P_0 represents the observed proportion of agreement between the two classifications, while P_e denotes the expected agreement by chance [22]. It has been interpreted that values of 0 indicate no agreement, 0.01–0.20 indicate slight agreement, 0.21–0.40 indicate fair agreement, 0.41–0.60 indicate moderate agreement, 0.61–0.80 indicate substantial agreement, and 0.81–1.00 indicate almost perfect agreement. [23-24]

In this modeling process, the 2020 LULC will be simulated by analyzing the LULC transition trends from 2010 (initial) to 2015 (final). The simulated 2020 LULC will then be validated against the actual 2020 LULC data. Once validated, the model will be used to project the LULC for 2030.

2.3 Soil Loss Estimation by RUSLE Model

Revised Universal Soil Loss Equation (RUSLE) is an enhanced model of the USLE. It is five-factor equation model that predicts the longtime average of annual soil loss that resulted from raindrop and runoff. Its components are sub-factorized to allow greater flexibility in calculating soil loss. The equation for the model [5] is:

$$A = R \times K \times LS \times C \times P \qquad \text{(Eq. 2)}$$

Where: A is the Annual Soil Loss Rate (t/ha/yr); R is the Rainfall Erosivity Factor (MJ/ha·mm/h); K is the Soil Erodibility Factor; LS is the Slope Length and Steepness Factor; C is the Land Cover (C) Factor; and P is the Support Practice (P) Factor.

a. R Factor

The Rainfall Erosivity (R) factor refers to the effect of rainfall on soil detachment and transport quantifying the kinetic energy exerted on land surfaces [25]. In this study, rainfall data from 2011-2021 was gathered from PAGASA. Annual average rainfall of three stations presented below were interpolated using inverse distance weighted (IDW) method to produce a rainfall distribution map of the Porac RB. R-factor was then calculated by using the R-factor equation of Dela Cruz et al. [26] which was specifically designed for the similar study site and catchments in tropical climate condition. The equation is presented in Eq. 3:

$$R = 0.1868 \times ARD \quad \text{(Eq. 3)}$$

Where *ARD* refers the average rainfall depth.

Table 2. PAGASA Rainfall Stations

Location	Latitude	Longitude
Clark, Pampanga	15.1717°	120.5617°
Iba, Zambales	15.3284°	119.9657°
Cubi Pt., Olongapo	14.7877°	120.2666°

b. K factor

Soil erodibility (K) factor represents the susceptibility of soil to erosion and transportability. This factor accounts for the properties of soil which includes the effects of texture, structure, mineralogy, organic matter contents and permeability to the ease of soil detachment and transportation during rainfall and surface flow [27]. K-factor values in this study were obtained by acquiring the soil map from the National Mapping and Resource Information Authority (NAMRIA) - GeoPortal Philippines (GeoPH) and adopting K-factor values from USDA-ARS [28].

c. LS Factor

Both topographic length and steepness of the site is significantly affecting the rate of soil loss. As discussed by Renard et al. [5], soil loss across a field may vary greatly from one point to another. For instance, on a long uniform slope, the soil loss at the top is much lower than at the bottom. This higher amount of soil loss at the bottom accounts to the detached, transported and deposited soil particles that runs through the slope. The LS factor in this study was calculated using a DEM, incorporating the LS formula developed by Desmet and Govers [29], which is given as:

$$L_{i,j} = \frac{\left(A_{i,j-in} + D^2\right)^{m+1} - A_{i,j-in}^{m+1}}{D^{m+2} \times x_{i,j}^{m} \times (22.13)^{m}} \quad \text{(Eq. 3)}$$

$$S = 10.8 \times sin\theta + 0.03 \; for\ slopes < 9\%$$

$$S = 16.8 \times sin\theta - 0.50 \; for\ slopes \geq 9\%$$

Where $L_{i,j}$ is the slope length factor for the grid cell at coordinates (*(i, j)*; $A_{i,j}$ is the contributing area, D is the grid cell size; *m* is a dimensionless exponent; and $x_{i,j}^{m}$ is the flow direction value raised to the power of m. The exponent *m* was calculated based on *S* conditions as follows: $m = 0.2$ for $S < 1\%$; $m = 0.3$ for $1\% \leq S \leq 3\%$; $m = 0.4$ for $3\% \leq S \leq 5\%$; and $m = 0.5$ for $S > 5\%$

d. C Factor

Land cover-management (C) factor refers to the ratio between the soil loss with its specified land cover and management [5]. A practical approach to determining the C factor involves referencing values from previous studies that assessed similar land cover types or were conducted in the same climatic and topographic condition [30]. In this case, the C factor values were adopted from Nut et al. [31], whose study area experiences the similar tropical climate.

Table 3. Values for C factor

LULC	C factor
Forests (FR)	0.001
Grasslands (GL)	0.08
Bare soil (BS)	0.35
Croplands (CL)	0.1
Built-up Areas (BU)	0.1

e. P Factor

The support practice factor (P) represents the ratio of soil loss under a specific soil conservation practice (e.g. contouring, terracing) of upslope and downslope tillage fields [5], Similarly, P factor values can be taken from literature. In this case, the P factor values was taken from Wischmeier & Smith [25] and further used by Sourn et al. [32] which uses the slope of cropland.

Table 4. Values for C factor

LULC	Slope %	P factor
Cropland	0 - 5	0.1
	>5 - 10	0.12
	>10 - 20	0.14
	>20 - 30	0.19
	>30 - 50	0.25
	>50 - 100	0.33
Other LULC	All	1

3. RESULTS AND DISCUSSION

Table 5. Pearson Correlation Values of Predictors

	Urban Distance	Roads Distance	River Distance	Forest Distance	Elevation	Pop. Density	Slope
Urban Distance		0.9865	0.9690	-0.8344	0.9426	-0.4576	0.6427
Roads Distance			0.9748	-0.8316	0.9355	-0.4313	0.6266
River Distance				-0.8222	0.9293	-0.4654	0.6064
Forest Distance					-0.8378	0.6246	-0.6852
Elevation						-0.4350	0.5867
Pop. Density							-0.4459
Slope							

3.1 Analysis of LULC Dynamics Prediction

3.1.1 Evaluating Correlation of Predictors

The correlation between the predictor variables was examined in the study using Pearson's Correlation Matrix. The correlation matrix reveals urban distance has a strong relationship with roads distance, river distance and elevation, suggesting that areas nearer the urban areas are also nearer from roads, and rivers, and tend to be located at lowest elevated regions. Forest distance shows strong negative correlations with urban distance, roads distance, and elevation. This implies that areas near the forests are generally found far away from the urban areas and roads, and located in the highest elevations. Slope is found to have a moderate correlation with elevation and urban distance, which suggests that steeper terrain is commonly found slightly elevated remote areas. Lastly, Population density shows weak to moderate negative correlations with urban distance, elevation and slope. This indicates that populations are concentrated in flatter, lower-lying areas closer to urban, roads and rivers.

3.1.2 Accuracy Assessment

Transition potential from 2010 to 2015 was modeled using Artificial Neural Network (ANN) learning process. Current validation kappa has resulted to 0.764, which indicates substantial agreement. However, transition validation between the simulated 2020 LULC and the actual 2020 LULC has yielded to a lower overall kappa value of 0.566 which indicates moderate agreement. The Kappa values for the histogram and location were 0.796 and 0.711, respectively. While the overall correctness reached 74.18%, suggesting that the majority of pixels were correctly classified, the Kappa statistic provides a stricter measure by accounting for agreement that could occur by chance.

3.1.3 LULC Classification

Table 6 presents the changes in LULC from years 2010, 2020, and 2030 (simulated). It can be noticed that there is a substantial increase of Built-up (BU) areas from 455.42 ha (4.01%) in 2010 to 810.43 ha (7.13%) in 2020 and is projected to reach 1,145.51 ha (10.08%) by 2030. These changes reflect to a total increase of 151.4% over the two decades which clearly indicates rapid urbanization. Forest (FR) area also exhibits an increase from 599.26 ha (5.28%) in 2010 to 818.60 ha (7.21%) in 2020 and is expected to increase at 1037.43 ha (9.13%) in 2030. As reported by PSA, statistics on land cover changes in the entire Philippines indicates an overall growth of 2.9% in forest cover. At regional level, the highest contribution of forest growth was recorded in Region III (Central Luzon) where the study area is located. Conversely, the cropland or agricultural land (CL) area has shown a declining trend with 4027.18 ha (35.45%) in 2010 to 2649.26 ha (23.32%) in 2020 and projected to shrink further to 2,224.72 ha (19.58%) in 2030. This decline in agricultural areas is supported by the study on Porac-Gumain Watershed [33] and Pampanga River basin [34]. It is reported that the decrease in agricultural area is attributed to the negative impacts of the Mount Pinatubo volcanic eruption affecting the soil fertility and irrigation productivity in Pampanga.

3.2 Soil Loss Analysis

3.2.1 RUSLE Factors

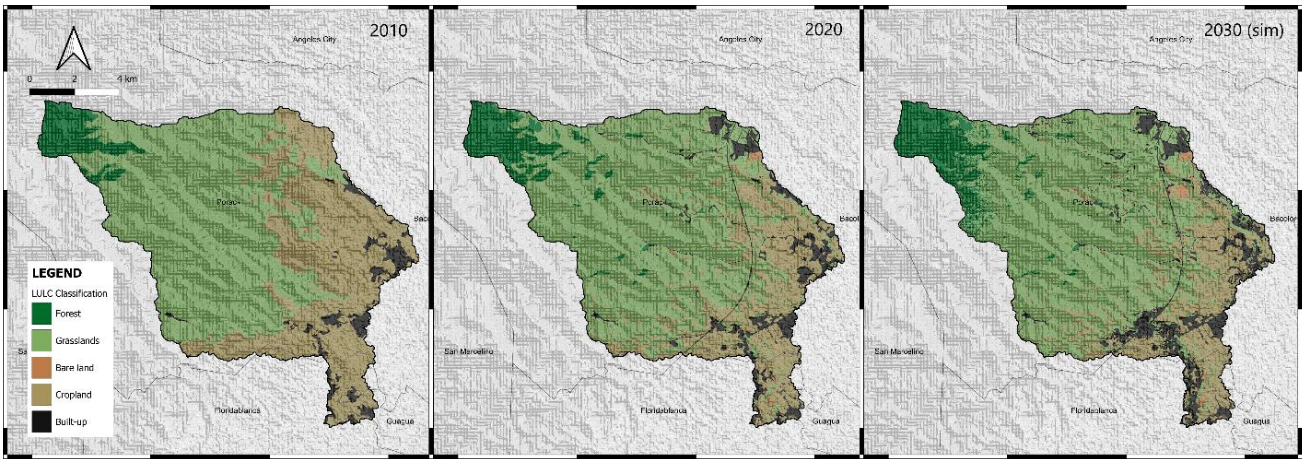

Figure 2. LULC Changes (2010 to 2030)

Table 6. LULC Area Changes and Percentage Distribution (2010–2030)

	2010		2020		2030	
LULC	Area (ha)	%	Area (ha)	%	Area (ha)	%
FR	599.26	5.275	818.6	7.206	913.26	8.039
GL	6277.39	55.257	7045.82	62.022	6277.39	60.89
BS	0.94	0.0082	36.08	0.317	70.35	0.64
CL	4027.18	35.449	2649.26	23.32	2080.11	18.31
BU	455.42	4.01	810.43	7.13	1379.29	12.14

The RUSLE factors were estimated using collected data and GIS software. Figure 3a shows the R factor rainfall erosivity map, which shows a minimum of 473.501 MJ mm ha^{-1} h^{-1} yr^{-1}, maximum of 539.593 MJ mm ha^{-1} h^{-1} $yr^{-1}$and an average annual R factor value of 511.356 MJ mm ha^{-1} h^{-1} yr^{-1} throughout the RB. Figure 3b shows the LS factor map, indicating that high LS factor values were predominantly found in the northwestern part of the basin, while lower values are mostly found in the southeastern region. From the estimation, a minimum value of 0.03 and a maximum value of 0. 111.41 was observed throughout the catchment. Figure 3c shows the K factor map, showing a dominant sandy soil texture classification at the site, which is equivalent to 0.1 t MJ− 1 h mm− 1 [28]. Sandy soil typically generates low surface runoff due to its high permeability, although it is highly susceptible to particle detachment. Figures 3d-f and Figures 3 g-I show the C factor maps and P factor maps, respectively, for the years 2010, 2020, and 2030. The C and P factor values were adopted from previous RUSLE studies with similar land cover types. In this study, the C factor was assigned as follows: 0.001 for FR, 0.35 for BS, 0.08 for GL (which cover most of the area), and 0.1 for both CL and BU areas. An average C factor values of 0.0837, 0.0814, and 0.0810 were observed in the LULC of years 2010, 2020, and 2030, respectively. On the other hand, P factor was assigned to be 0.1 on agricultural land (0.5% slope) and 1.0 on other covers considering that there is no support practice observed. It resulted in average values of 0.682. 0.789, and 0.835 in the LULC of the years 2010, 2020, and 2030, respectively.

Among all the factors in the RUSLE model, the C and P factors are directly influenced by land use and land cover (LULC) changes. Variations in LULC have led to slight changes in the mean values of the C and P factors across the entire RB. This can be attributed to the expansion of urban areas in the flatter regions and the simultaneous increase in forest cover in the northern part of the basin. The growth in forest areas is largely due to the ongoing efforts of the Department of Environment and Natural Resources (DENR) under the Enhanced National Greening Program [DENR], which has been actively rehabilitating forests since 2011. In addition, there was a significant decrease in agricultural land within the basin, which, as previously discussed, is attributed to the impact of volcanic eruptions on soil fertility.

3.2.2 Soil Loss

Soil loss modeling in different LULC scenarios using the RUSLE model shows variations in the average annual soil loss from 2010 to 2030, as presented in Figures 4a-c. The average annual soil loss was estimated at 15.10 t $ha^{-1}yr^{-1}$, 15.31 t $ha^{-1}yr^{-1}$, and 15.46 t $ha^{-1}yr^{-1}$ in 2010, 2020, and 2030, respectively. Although there is a significant expansion of BU in the lower region of the basin which attributes to higher C and P factor values, it has been offset by the continuous increase of FO in the higher region with contrastingly containing the lowest C factor value of 0.001. On the other hand, standard deviation of soil loss was calculated at 18.17 t $ha^{-1}yr^{-1}$, 17.43 t $ha^{-1}yr^{-1}$, and 17.22 t $ha^{-1}yr^{-1}$ in year 2010, 2020, and 2030, respectively. The decrease in the standard deviation denotes a smaller range of erosion rates within the basin, suggesting that soil loss might be becoming more spatially consistent, attributing to the expansion of FR and BU areas on both end sides of the basin, along with the reduction in CL areas.

Table 7: Summary of Mean and Standard Deviation of Annual Soil Loss (t ha^{-1} yr^{-1}) for 2010, 2020, and 2030.

Year	2010	2020	2030
Mean	15.10	15.31	15.46
Std. Dev.	18.17	17.43	17.22

Figures 6a-c presents the soil loss maps of the RB from 2010, 2020, and 2030. The middle region of the catchment is experiencing high amounts of soil loss and slightly extending towards the bottom areas. These specific regions are characterized with the highest LS factor values, which is the most influential factors of soil erosion [35]. Runoff that occurs on these slopes generates greater kinetic energy, which enhances erosive and transport power and leads to intensified soil loss [36]. Moreover, the slight increase in the soil loss observed in the lower elevated regions is attributed to the expansion of BU which increases the impervious surfaces leading to reduced infiltration. Lower infiltration leads to stormwater runoff peaks that are higher in magnitude and shorter in duration [2] which subsequently affects the sediment dynamics [3]. It has been shown in correlation analysis studies the significant evidence of a strong positive relationship between runoff and sedimentation [4].

While the change in LULC, particularly the transition to BU may not be as influential as topographic slope in determining critical areas for soil loss, LULC change remains significant because it is a factor that can be managed or altered by humans. It has been evident that human intervention has had a positive impact, particularly through the continuous efforts of afforestation which significantly helped to balance the mean soil loss across the entire basin. The RUSLE modeling conducted in this study has effectively identified critical areas vulnerable to soil erosion, revealing an increasing trend associated with the expansion of impervious surfaces such as urban and built-up areas. This further emphasizes the necessity of integrated watershed management strategies and policies [37], not only for flood mitigation and runoff control, but also the control of soil erosion and sediment deposition [38].

4. CONCLUSION

This study has demonstrated the use of MOLUSCE and RUSLE in assessing land use changes and their impact on soil erosion dynamics. The correlation analysis has found the relationship between predictors (Urban Distance, Roads Distance, River Distance, Forest Distance, Elevation, Population Density, and Slope). These predictors were used to model the transition potential using Artificial Neural Network (ANN) learning process which resulted in an overall kappa value of 0.566 suggesting moderate correlation. LULC modeling has presented significant changes between 2010 and 2030. Built-up (BU) areas have expanded rapidly, increasing by over 150%, indicating accelerated urbanization. Forest (FR) cover also shows steady growth, aligning with government efforts of reforestation. In contrast, cropland (CL) has markedly declined, largely

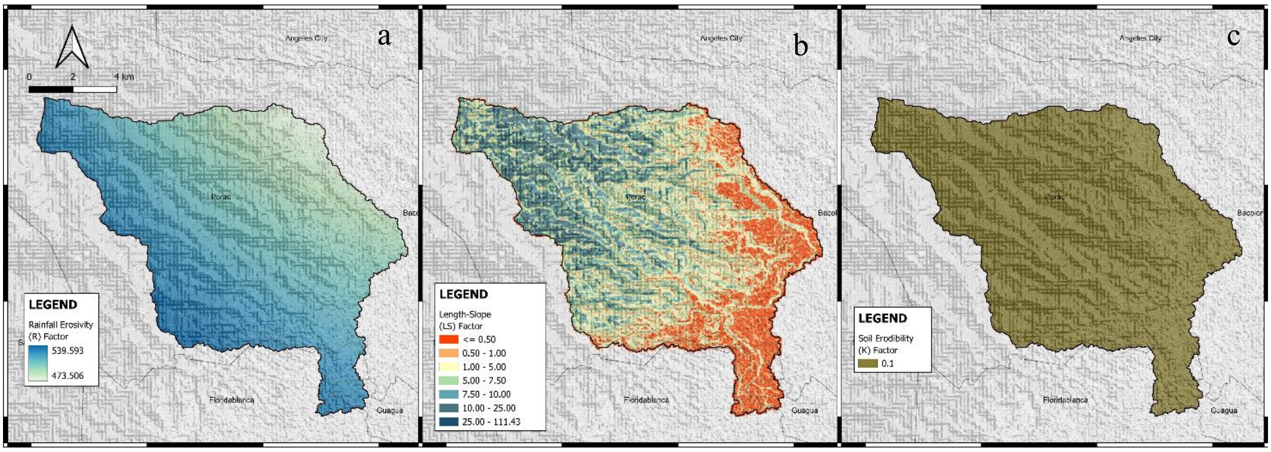

Figure 3a-c. R, LS, and K Factor Maps

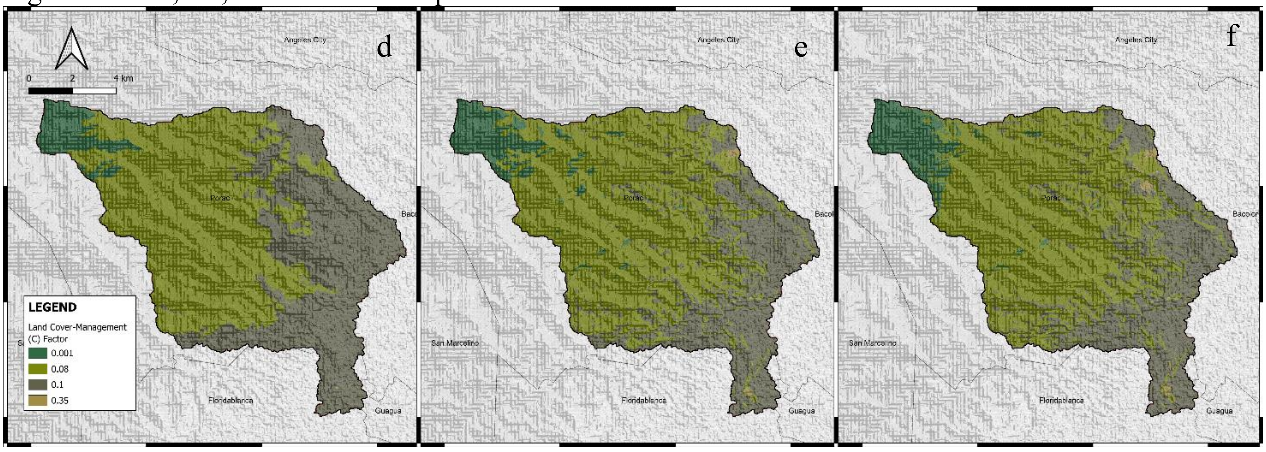

Figure 3d-f. C Factor Maps (2010, 2020, and 2030)

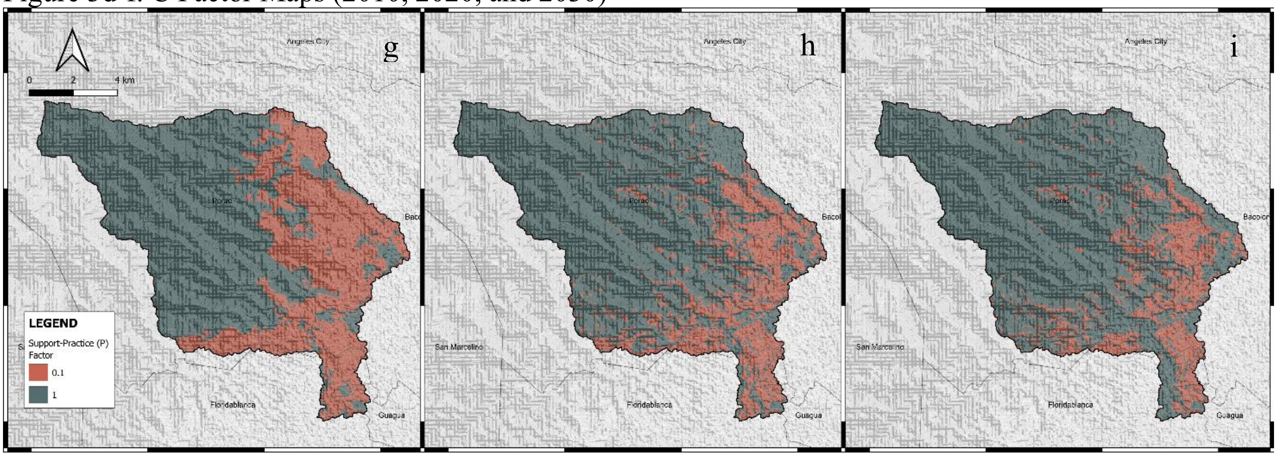

Figure 3g-i. P Factor Maps (2010, 2020, and 2030)

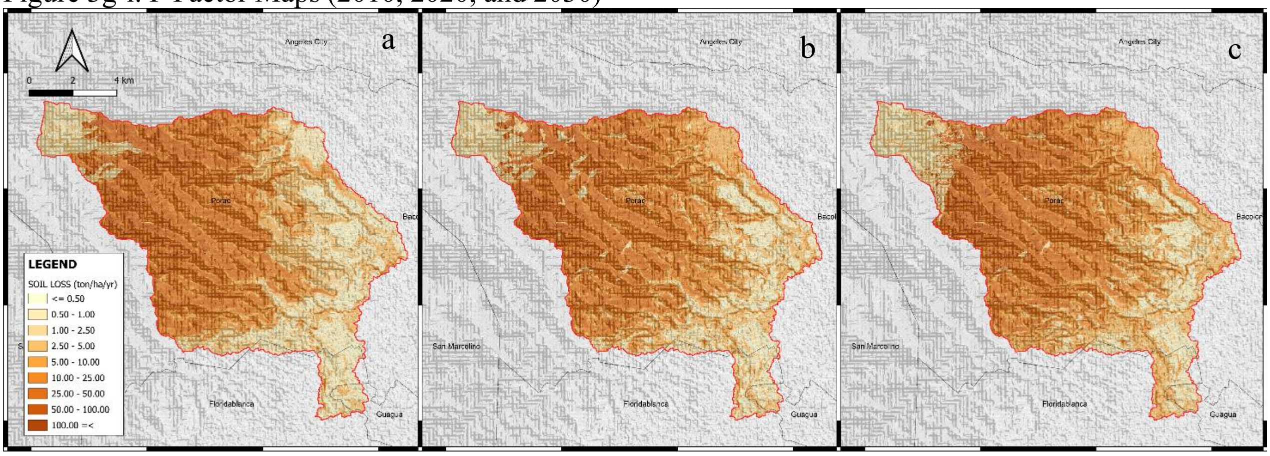

Figure 4. Soil Loss Maps (2010, 2020, and 2030)

due to the long-term effects of the Mount Pinatubo eruption on soil fertility and irrigation in the region. RUSLE-based soil loss modeling from 2010 to 2030 showed a slight increase in average annual soil erosion, while variability in erosion rates decreased. This trend reflects the combined influence of expanding built-up areas in lowland regions and increasing forest cover in upland areas, which helped offset potential soil loss. Although LULC change, particularly urban expansion, is less influential than slope in driving soil erosion, it remains a critical and manageable factor. Human interventions, especially reforestation have contributed positively by helping stabilize average soil loss. The result from this study contributes to the limited study on LULC changes particularly in the Philippines. Since, MOLUSCE is a newly established model, its validity is still continuously developing. Its integration with RUSLE model which predicts soil loss gives an overview on how land cover develops over time and how it affects the sediment dynamics. This can provide substantial inputs for rehabilitation and restoration of natural environment alongside with the policymakers of sustainable watershed management.

5. ACKNOWLEDGEMENT

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