
評估濁水溪集水區水土保持之水土流失、
逕流和土地利用方案之研究

Research on assessment of soil erosion,
runoff and establishment of land use
scenarios for soil-water conservation at
Zhuoshui River Basin

執行單位：國立中央大學

執行期間：109 年 02 月 06 日至 109 年 12 月 31 日

計畫主持人：劉說安 教授

行政院農業委員會水土保持局 編印

中華民國 109 年 12 月

(本報告書內容及建議純屬執行單位意見，僅供本局施政參考)

評估濁水溪集水區水土保持之水土流失、逕流和土地利用方案之研究

摘要

台灣山區水土遭受大量降雨和暴雨的影響，以致經常發生土壤侵蝕和山崩等災害。這些天然災害除了直接造成生命財產的損失外，也會加速土壤的退化，並影響土壤生產力、作物產量以及農業永續發展。因此，本計畫目標為量化土地利用比例及其對土壤侵蝕、沉積物產量和逕流的影響，並且考慮逕流與山崩事件之間的連結，探討地表逕流深度與山崩發生的關係。為了獲得預期的結果，將透過一些經驗模式（如 RUSLE (Revised Universal Soil Loss Equation)、SCS-CN 曲線(Soil Conservation Service - Curve Number)）及遙測和 GIS 技術模擬出土壤侵蝕、沉積物產量和逕流。

結果顯示，從 RUSLE 模型獲得的長期年土壤流失率在 0.00 到 6,881.88 t ha⁻¹ yr⁻¹ 之間，2005 年至 2019 年平均為 122.94 t ha⁻¹ yr⁻¹。總面積的一半以上被歸類為中等和中等嚴重流失，整個盆地的三分之一為嚴重和非常嚴重流失。再者，使用擬和的 RUSLE-SDR 模型估算每個子流域的泥沙產量(sediment yield; SY)，預測的所有上游年平均 SY 約為 246.06 (106 t yr⁻¹)，預測和觀測到的 SY 之差為 24.47

%。此外，結果表明，在此研究期間（2005-2019 年），土壤侵蝕速率已逐漸降低。一般而言，大面積地區遭受中度和中度嚴重危害，佔總數的 50% 以上，輕度侵蝕佔 15% 以上，其餘百分比則分為嚴重和非常嚴重的危害。在逕流估算方面，近 15 年全流域地表逕流略有減少，山崩主要發生在坡面，地表逕流值超過 3000 mm yr⁻¹。

本研究採用了台灣的坡地能力分類（SLCC），其中一個輸入來自 2019 年的 RUSLE 結果。LULC（土地利用/土地覆蓋）方案是基於 SLCC 和 LULC 在 2019 年之間的考慮而得出的。因此，除了目前之 LULC（方案 1），建議進行三種 LULC 方案的調整，包括 SLCC（方案 2）之後的 LULC 轉換，農業發展與生態環境保護之間的權衡（方案 3）和生態環境優先（方案 4）。這些 LULC 方案分為三種類型的措施，將為地方當局或利益相關者提供充分的選擇，以優化濁水溪流域內的土地資源利用。該項目的成果有望提供參考資訊，以用來協助設計土地利用方案或調整土地利用計畫與決策，並減輕濁水溪流域的土壤侵蝕和山崩造成的災害。

關鍵詞：土壤侵蝕、RUSLE、SCS 曲線數、土地利用方案

Research on assessment of soil erosion, runoff and establishment of land use scenarios for soil-water conservation at Zhuoshui river basin

Abstract

Mountainous areas have been suffering from soil erosion and landslide processes, particularly in the tropical humid areas. Taiwan annually receives a large amount of rainfall and rainstorms during the rainy season. Natural hazards can accelerate the soil resource deterioration and result in impact on the soil productivity, crop yield, and long-term sustainable agricultural development. Therefore, this project aims to quantify land use dynamic and its effect on soil erosion, sediment yield, and runoff. The relationship between runoff and landslide events will be also considered to examine how surface runoff depth correlates with landslide occurrence. To achieve the expected objectives, Geographic Information System (GIS) and remote sensing (RS) techniques will be integrated with the RUSLE (Revised Universal Soil Loss Equation) model and SCS-CN (Soil Conservation Service) curve number to simulate soil erosion, sediment yield, and runoff.

Results show that the long-term annual soil loss rate obtained from the RUSLE modeling ranges from 0.00 to 6,881.88 t ha⁻¹ yr⁻¹ with an average rate of 122.94 t ha⁻¹ yr⁻¹ from 2005 to 2019. Over one half of the total area is categorized as *moderate* and *moderately severe* classes, and one third of the whole basin as *severe* and *very severe* classes. After that, the coupled RUSLE-SDR model was used to estimate the sediment yield (SY) at each sub-basin. The predicted annual SY accounting for all upper streams is about 246.06 (10⁶ t yr⁻¹), and the difference between the predicted and observed SYs is 24.47%. Furthermore, results highlight that the soil erosion rate has been gradually reduced during the study period (2005-2019). In general, large areas

suffered from moderate and moderate severe classes with over 50% of the total, mild erosion accounting for over 15% and the remaining percentage falling into severe and very severe classes. As for the runoff estimation, there is a slight decrease in the surface runoff for the whole basin in the last 15 years and landslide occurrence mainly happened on the hilly slope with surface runoff value over 3000 mm yr⁻¹.

This study adapted Slope Land Capability Classification (SLCC) for Taiwan, in which one input comes from the RUSLE result in 2019. LULC (land use/land cover) scenarios were based on the consideration between SLCC and LULC in 2019. Consequently, besides the current LULC (scenario 1), three LULC scenarios were recommended for its adjustment, including LULC transformation following SLCC (scenario 2), trade-off between agricultural development and eco-environmental protection (scenario 3), and eco-environmental priority (scenario 4). These LULC scenarios are three types of measures valuable for the local authorities or stakeholders in optimizing the utilization of land resources within the Zhuoshui River Basin. Implementation of the suggested measures is expected to assist in adjusting land use planning and land use policy to reduce soil erosion and landslide in the Zhuoshui River Basin of Taiwan.

Keywords: Soil erosion, Soil delivery ratio, RUSLE, SCS curve number, Land use scenarios, Zhuoshui River Basin

Table of contents

摘要.....	I
Abstract.....	III
Table of contents.....	V
List of Tables.....	VII
List of Figures.....	IX
Chapter 1 Introduction	1-1
Chapter 2 Implementation method and steps.....	2-1
2.1 Implementation method	2-1
2.2 Steps	2-4
Chapter 3 Progress and work package.....	3-1
3.1 Gantt chart.....	3-1
3.2 Work package.....	3-3
3.2.1 Data of Work Package 1	3-3
3.2.2 Methodology of Work Package 1.....	3-7
3.2.3 Result of Work Package 1	3-14
3.2.4 Introduction of Work Package 2	3-19
3.2.5 Material of Work Package 2.....	3-20
3.2.6 Methodology of Work Package 2.....	3-21
3.2.7 Result of Work Package 2	3-30
3.2.8 Introduction of Work Package 3	3-43
3.2.9 Material of Work Package 3.....	3-43
3.2.10 Methodology of Work Package 3.....	3-44
3.2.11 Result of Work Package 3	3-48
3.2.12 Conclusion of Work Package 3.....	3-59
3.2.13 Introduction of Work Package 4	3-60

3.2.14	Mapping slopeland capability classes of Work Package 4	3-62
3.2.15	Establishing land use scenarios to reduce soil erosion of Work Package 4	3-66
3.2.16	Discussion and Conclusion of Work Package 4	3-72
Chapter 4	Conclusions and Suggestions.....	4-1
4.1	Conclusions.....	4-1
4.2	Suggestions	4-3
References		5-1
Appendix		Appendix1-1
	Appendix1: Comments and Replies	Appendix1-1
	Appendix 2: Photos from field survey.....	Appendix2-1

List of Tables

Table 1. Attributes of Zhuoshui River Basin	1-2
Table 2. Land use dynamic from 1998 to 2013	1-3
Table 3. Landsat 8 images used in this project (2019).....	3-4
Table 4. Landsat 5 images used in this project (2011).....	3-5
Table 5. Landsat 5 images used in this project (2005).....	3-5
Table 6. Land-cover transfer matrix from 2005 to 2019.....	3-16
Table 7. Land-cover transfer matrix from 2005 to 2011.....	3-17
Table 8. Land-cover transfer matrix from 2011 to 2019.....	3-17
Table 9. K value extracted from KI value based on Taiwanese soil types	3-23
Table 10. C value for three different years.....	3-32
Table 11. P value for three different years	3-34
Table 12. Soil erosion rate for three different years.....	3-34
Table 13. Classification of soil erosion rate	3-36
Table 14. Soil loss rate ($\text{t ha}^{-1} \text{ yr}^{-1}$) at different LULC.....	3-37
Table 15. Sediment delivery ratio for each sub-basin.....	3-38
Table 16. The predicted sediment yield obtained from three SDR equations.	3-38
Table 17. Annual suspended sediment discharge at gauge stations.....	3-39
Table 18. Model performance statistics.....	3-40
Table 19. Hydrologic soil group (HSG) for USDA soil texture classes	3-46
Table 20. CN value base on HSG and land cover.....	3-47

Table 21. Runoff classification into 7 classes	3-47
Table 22. The CN values for three difference years	3-50
Table 23. The S values for three difference years.....	3-52
Table 24. The accumulated annual runoff values from 2005 to 2019	3-54
Table 25. Model performance statistics	3-56
Table 26. The frequency ratio of LS on each class of runoff.....	3-58
Table 27. Data used to mapping slopeland capability classification	3-62
Table 28. Input parameters for slopeland capability classification.....	3-62
Table 29. Land capability class and its treatments.....	3-65
Table 30. Percentage of each LULC according to SLCC	3-67
Table 31. Scenario 2 for LULC transformation in accordance with SLCC.....	3-68
Table 32. Scenario 3 for LULC transformation in accordance with SLCC.....	3-70
Table 33. Scenario 4 for LULC transformation in accordance with SLCC.....	3-71
Table 34. Summarizing LULC transformation matrix for scenario 2,3,4.....	3-72

List of Figures

Figure 1. Zhoushui River Basin	1-1
Figure 2. Mean sediment yield and cumulative hyperpycnal discharge.....	1-4
Figure 3. Relationships between landslide number and cumulative rainfall	1-5
Figure 4. Proposed assessment framework.....	2-1
Figure 5. Scenes of Landsat image covering the study area	3-4
Figure 6. Digital Elevation Model	3-6
Figure 7. Slope	3-6
Figure 8. Hill Shade	3-6
Figure 9. Road Density	3-6
Figure 10. Flowchart of LULC classification	3-7
Figure 11. Band combination for better visualization	3-8
Figure 12. Indices for aiding sample selection	3-9
Figure 13. Sample distribution of the year 2005.....	3-10
Figure 14. Sample distribution of the year 2011.....	3-11
Figure 15. Sample distribution of the year 2019.....	3-11
Figure 16. Finding the number of trees (n-estimators)	3-13
Figure 17. Finding the max-depth hyperparameter.....	3-13
Figure 18. The confusion matrix of the year 2011.....	3-14
Figure 19. LULC map of the year 2005.....	3-15
Figure 20. LULC map of the year 2011.....	3-15
Figure 21. LULC map of the years 2019	3-18
Figure 22. Annual rainfall map & rainfall stations	3-22
Figure 23. Taiwan soil types	3-24
Figure 24. The flowchart of summarizing steps	3-27

Figure 25. Rainfall erosivity	3-30
Figure 26. Soil erodibility	3-31
Figure 27. Slope and length factor	3-31
Figure 28. Average C value of 2005	3-32
Figure 29. Average C value of 2011	3-32
Figure 30. Average C value of 2019	3-33
Figure 31. Soil loss rate of the year 2005	3-35
Figure 32. Soil loss rate of the year 2011	3-35
Figure 33. Soil loss rate of the year 2019	3-36
Figure 34. Components of SCS runoff equation.....	3-45
Figure 35. The soil taxonomy of the Zhuoshui River Basin.....	3-46
Figure 36. Flow chart to assess the relation between runoff and landslide	3-48
Figure 37. The CN value of 2005	3-49
Figure 38. The CN value of 2011	3-49
Figure 39. The CN value of 2019	3-50
Figure 40. The S value of 2005.....	3-51
Figure 41. The S value of 2011.....	3-51
Figure 42. The S value of 2019.....	3-52
Figure 43. The runoff distribution in 2005	3-53
Figure 44. The runoff distribution in 2011	3-53
Figure 45. The runoff distribution in 2019	3-54
Figure 46. Mean of accumulated annual runoff.....	3-55
Figure 47. Sub-basins of the Zhuoshui River Basin	3-56
Figure 48. Landslide and runoff in 2005.....	3-57
Figure 49. Runoff classification and LS occurrence in 2006.....	3-58
Figure 50. The long-term frequency ratio of LS occurrence on runoff	3-59

Figure 51. Slope gradient classes	3-63
Figure 52. Soil depth classes	3-63
Figure 53. Slopeland Classification adapted from SWCB.....	3-64
Figure 54. Spatial distribution of SLCC in the study area.....	3-65
Figure 55. LULC scenario 1	3-67
Figure 56. LULC scenario 2	3-69
Figure 57. LULC scenario 3	3-70
Figure 58. LULC scenario 4	3-71

Chapter 1 Introduction

The Zhuoshui River, also called Choshui River, (濁水溪) is the longest river in Taiwan. Its headwater originates from the west part of the central mountain range belonging to the Nantou County and it travels through three counties (Changhua, Chiayi and Yunlin) before joining into the Taiwan Strait. The main stream of the Zhuoshui River Basin (ZRB) is about 187 km in length and this basin covers an a total area of 3200 km² [1]. The river is considered as an natural boundary between the north and south of Taiwan.

There are seven main attribute streams that contribute to the Zhuoshui River. These streams originate from high mountains, bringing flow and sedimentation to the mainstreams. Figure 1 shows the Zhuoshui River Catchment [2], primarily expanding over two counties Changhua and Yunlin with seven main attribute streams.

The upper flow of the Zhuoshui River is controlled by the Wushe Dam (霧社水庫), Wujie Dam (武界壩), and further downstream by the Chichi Weir (集集攔河堰). Table 1 lists the attributes of the Zhuoshui River, including streams, length, elevation, valley slope, and average valley width. It also provides most of the water resources and hydroelectric power generation in the central Taiwan. In addition, natural disasters and land resource utilization in the Zhuoshui River Basin are closely related to the lives and property of the people of Taiwan.

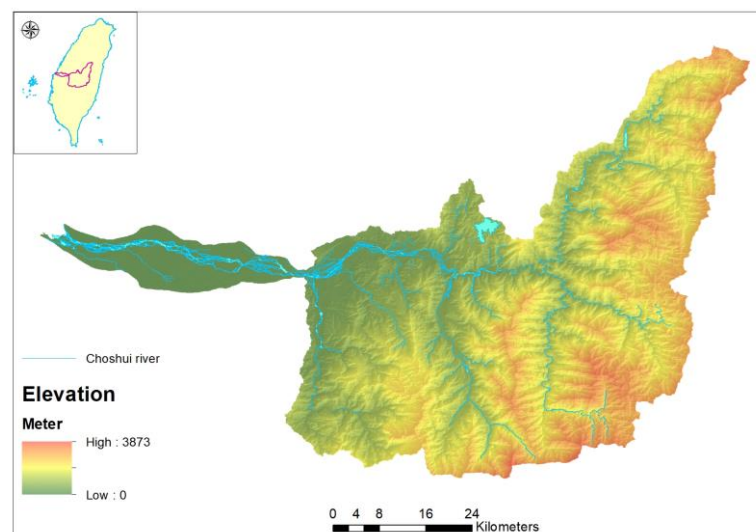


Figure 1. Zhuoshui River Basin.

Table 1. Attributes of Zhuoshui River, including upstream boundary, elevation, valley slope, and average valley width [2].

Upstream Boundary	Elevation (m)	Valley slope	Average valley width (m)
Confluence of Alibudong Stream (阿里不動溪流域會合處)	586 – 708	0.0219	303
Confluence of Shibachong Stream (十八重溪流域會合處)	440 – 586	0.0183	376
Confluence of Junkeng Stream (郡坑溪流域會合處)	308 – 440	0.0165	481
Confluence of Chenyoulan Stream (陳有蘭溪流域會合處)	266 – 308	0.0079	450
Confluence of Shuili Stream (水里溪流域會合處)	196 – 266	0.0076	730
Jiji Weir (集集攔河堰)	152 – 196	0.0065	364
Mingzhu Bridge (名竹大橋)	99 – 152	0.0072	1000
Confluence of Qingshui (清水溪流域會合處)	52 – 99	0.0046	1514
Dazhuang Village (大庄村)	16 – 52	0.0021	1083
Ziqiang Bridge (自強大橋)	0 – 16	0.001	1448

With settlement expansion, population growth, and economic development, land use in the study area has been varying significantly, especially in the impervious and agricultural areas. According to Fu et al. [4], between 1998 and 2013, built-up land was increased by 51.91% from 1990 ha in 1998 to 3023 ha in 2013 and bare land also had a similar trend with an increase by 21% (from 8,551 ha in 1998 to 10,347 ha in 2013) (Table 2).

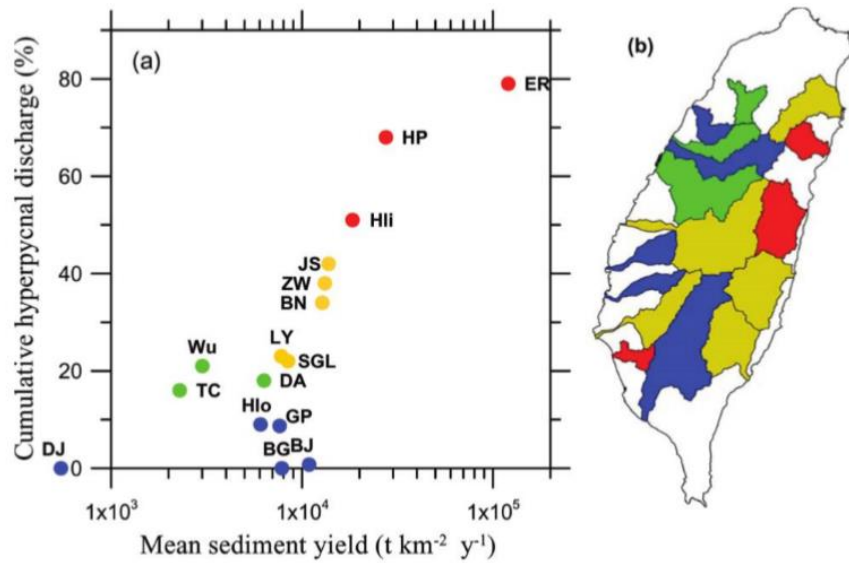
The above mentioned increasing trends result in speeding up surface runoff on the slope lands and impervious areas, and increase the soil loss on the mountainous areas and sediment deposition in downstream, and finally accumulation in dams. As a result,

sediment yield can affect the storage ability, and reduce the timely activity of dams or reservoirs. Chiang et al. [3] assessed the variation of sediment export from various Taiwan watersheds showing that the Zhuoshui River Basin produces the highest amount of sediment loads compared to the other river basins (such as Tamshui, Zengwen, Gaoping, and Hualien) in Taiwan.

Table 2. Land use dynamic from 1998 to 2013 in the Zhuoshui River Basin [4].

Land use types	1998 (ha)	2003 (ha)	2008 (ha)	2013 (ha)	Change ratio (1998-2013)
Water	12,264	12,284	12,170	12,173	-0.74%
Built-up land	1990	2792	2802	3023	51.91%
Bare land	8551	9650	14,561	10,347	21.00%
Vegetation	277,445	275,524	270,717	274,707	-0.99%

A vast amount of sediment generation mainly results from the geological characteristics and its geographical distribution to receive the impacts of landslides, typhoons, and heavy precipitation that provide a large amount of water and sediment to the river [3]. Kao and Milliman [5] investigated annual sediment discharge for the 16 rivers in Taiwan and showed that sediment load into Taiwanese rivers annually fluctuates from 0.5 Mt yr⁻¹ (Dajia River for 25 years of measured data) to 40 Mt yr⁻¹ (the Zhuoshui River based on 42 years of observed data). The average annual sediment yield for 16 river basins is 9,500 t km⁻² yr⁻¹, approximately 60 times higher than the global average around 150 t km⁻² yr⁻¹ [5]. Because of steeper-gradient drainage, east coast river basins tend to have a higher sediment yield (average of 12,000 t km⁻² yr⁻¹; 13,000 t km⁻² yr⁻¹ for elevation above 100 m) than west coastal river basins (6,800 t km⁻² yr⁻¹) [5]. As seen in Fig. 2, the average sediment yield in the Zhuoshui River Basin is much higher in comparison to the other rivers (14,000 t km⁻² yr⁻¹), just behind Erren River, Hoping River, and Hualien River.



a, Cumulative percent hyperpynal flow in total sediment discharge against sediment production per unit area (in T km⁻² yr⁻¹) for >100 m elevations for 16 rivers. Values are based on full record periods. River names: BG = Beigang, BJ = Bajhang, BN = Beinan, DA = Daan, DJ = Dajia, ER = Erren, GP = Gaoping, Hli = Hualien, Hlo = Houlong, HP = Hoping, JS = Jhuoshuei, LY = Lanyan, SGL = Siouguluan, TC = Toucian, Wu = Wu, and ZW = Zengwun. *b*, Watersheds are colored as categorized by criteria in *a*.

Figure 2. Mean sediment yield and cumulative hyperpynal discharge for 16 Taiwanese river basins above 100 m elevation [5].

In fact, water erosion can result in slope increase over time, particularly in the affected areas and then shallow landslide is accelerated. Mountainous regions receive the most devastating kind of water erosion, where unstable material can result in the mass movement of soil and rock [6].

The prediction of surface runoff and its comprehensive understanding can explain the magnitude and amount of surface erosion and slope instability over the space. When runoff increases due to lack of infiltration surfaces like forests or other vegetation types, it enables the surface to be eroded or leads to landslides and debris flows on steep slopes. Runoff is considered as a contributing factor that can be stood for some topographic factors in landslide susceptibility assessment [3]. In addition, Taiwan annually receives heavy rainfall caused by typhoons (approximately 3.6 typhoons every year) so that runoff may be the most triggering factor that contributes to landslide hazards.

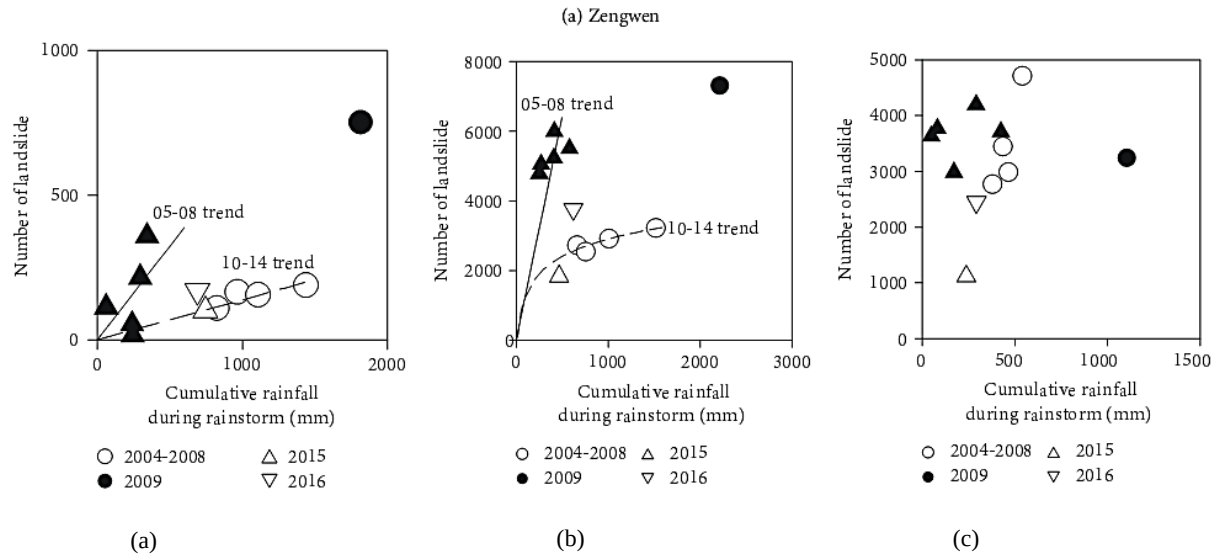


Figure 3. The relationships between the landslide number and cumulative rainfall in Zengwen, Gaoping, and Zhuoshui river basins [7].

Hung et al. [7] assessed the impacts of extreme typhoon events on sediment discharges and landslides in the mountainous regions of Taiwan. From Fig. 3, it is obvious that cumulative rainfall during a rainstorm in the Zhuoshui River Basin is lower than the other two basins, but the number of landslide events stands at the second after Gaoping River Basin. In 2009, when Typhoon Morakot hit Taiwan with total rainfall over 1,000 mm in the Zhuoshui River Basin, and caused a large number of landslides (over 3,000 landslides). Recently, runoff-depth was studied, showing a connection to landslides. Chan et al. [8] investigated the rainfall-runoff and landslides in unsaturated soil showing that the depth of runoff flow may be used as a predictor instead of the rainfall depth or maximum rainfall intensity.

Research on assessment of soil erosion, runoff and establishment
of land use scenarios for soil-water conservation at Zhuoshui river basin

Chapter 2 Implementation method and steps

2.1 Implementation method

In this study, hydrological and soil erosion models, remote sensing technology, and GIS tools are employed to design the presentation of the tabulation and mapping soil loss, runoff, and sediment yield following the time series. Figure 4 shows the overall proposed assessment framework, mainly consisting of the use of hydrological and soil erosion models, and remote sensing data (RS) and GIS techniques with the corresponding implemented methodological steps.

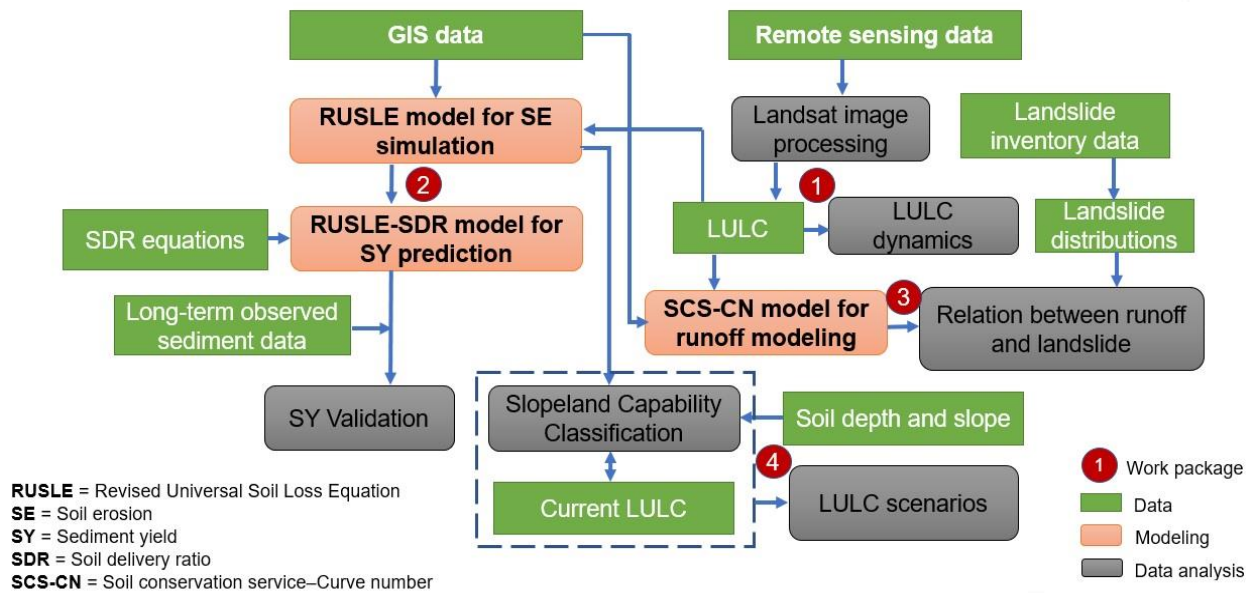


Figure 4. The proposed assessment framework, mainly consisting of the use of hydrological and soil erosion models, and RS data and GIS techniques with the corresponding implemented methodological steps.

Involved main methods and steps for the completion of the proposed work, including the methods used, difficulties to encounter and their possible solutions, and the use of important instruments and equipments, are detailed below.

To estimate the soil erosion rate, the USLE (Universal Soil Loss Equation) model is the most well-known model applied by various researches in many regions over the world [9]. Thus, academics as well as government agency employ this empirical formula to predict the soil erosion. The USLE is recommended as a standard soil loss estimation model in the Soil and Water Technical Regulations published by the Council of Agriculture, Government of Taiwan [10]. The model then was developed to become the revised version, now known as Revised Universal Soil Loss Equation (RUSLE), to further improve its ability to predict the water erosion. The RUSLE is still widely used because of its advantages in the combination of remote sensing and GIS techniques to simulate the rate and spatial distribution of erosion.

Input files for the RUSLE model include:

- Land use types
- Cover and management factor
- Rainfall and runoff factors or rainfall erosivity
- Soil erodibility factor
- Topographic factor (slope length and slope steepness).
- Conservation practice factor.

Output files for the RUSLE model include:

Annual soil erosion at the watershed scale.

The land use/land cover (LULC) type as an important input of the RUSLE can be obtained from the multi-temporal high resolution satellite images covering the study area. Landsat satellite image is a good choice to classify the land use/land cover for the analysis of its dynamics. In the RUSLE, cover and management practice show a significant role in controlling the soil erosion rate, represented by the C and P factors. The C factor is perhaps the most important input concerning policy and land use decisions that can be easily adjusted to decrease erosion [11]. Therefore, the C factor incorporates the support practices, such as contour farming, terracing, strip cropping etc. Such incorporation can be considered as the method to establish land use scenarios for mitigating soil erosion rate.

Until now, there are various empirically- or physically-based models (AGNPS, EUROSEM, HSPF, SEDNET, WEPP, USLE, SHESED, etc.) to model the sediment yield (SY), which is the amount of sediment lost by soil erosion from a river basin during a given period [12]. After simulating the soil erosion by using the RUSLE, the sediment yield will be estimated for the entire river basin and sub-basins. The most widely-used approach to predict the sediment yield from a watershed is to combine soil erosion model and sediment delivery ratio (SDR). There are numerous empirical equations to quantify the sediment yield travelling into the outlet of a watershed, sub-watershed or reservoir, such as those equations or models developed by Khosla [13], Garde and Kothyari [14], Flaxman and Elliott [15], etc. In Taiwan, various researchers applied different methods to identify the sediment yield (SY) of a watershed. For example, statistical methodology was already employed by Wu [16] for 79 stations throughout Taiwan ($SY = 3080A^{1.154}$), and by Chen et al. [16] for major reservoirs in Taiwan ($SY = 0.424A^{0.8982}$) to establish the relationship between SY and watershed area (km^2). There are others developed empirical models for sediment delivery ratio (SDR) with multi-factors such as watershed size, river density, relief ratio, etc. For example, Chen [16] proposed a regression equation $SDR = -29.1 + 110.2(S_0/S_a) + 112.8 (R/L)$ for the Zhuoshui River Basin. From the previously-developed empirical equations in Taiwan, this study combines soil erosion rate estimation by using the RUSLE and SDR to obtain the SY at the river basin scale.

To check the modeled results, the observed data at gauge stations or dams need to be collected, especially sediment yield. After that, model validation will be done for the total sediment yield value (t yr^{-1}) by using the Nash and Sutcliffe criterion or PBIAS that is commonly used in hydrological modeling. This study uses sediment discharge at the outlets of the modeled basin as reference data.

At the present, there is a wide range of approaches in researching landslide assessment and prediction, in which Soil Conservation Service (SCS) Runoff Curve Number (CN) model proposed by United States Department of Agriculture (USDA, 1972) is intensively applied in hydrology and water resource planning of agricultural areas in the United States and other countries as well. This model estimates runoff by

integrating soil type, land use/treatment, surface condition, and antecedent moisture condition [17]. The advantage of this model is that it can provide the user a wide range of choice in land development and then assess the impacts of use scenarios might have. The model is initially developed to predict runoff volumes at agricultural fields and small watersheds. In the present, it is also applied to evaluate landslide potentiality in the basin. USDA [18], for example, employed the model to determine the surface runoff from 6 sub-basins for spatially simulating the distribution of slope instability and soil erosion. Landslide Potentiality Index Value (LPIV) was derived for each sub-basin to assess the sub-basins prone to landslides. In this study, runoff estimation by using the model will be used to assess the magnitude of surface runoff and correlation analysis between the degree of surface runoff with observed landslide events by using frequency ratio method.

As for LULC scenarios in supporting watershed management, we adapted Slope Land Capability Classification (SLCC) in Taiwan [19] as basic information, together with current LULC (2019) to propose LULC scenarios. These LULC scenarios will provide alternative choices for planners or local authorities to mitigate soil erosion rate at the basin.

2.2 Steps

To achieve the goals and objectives, the project is implemented by steps as addressed below:

1. Collect the data, including the digital elevation map, soil map, land use maps, long-term annual rainfall, suspended sediment and water discharge at gauge stations; and temporal satellite images;
2. Process the temporal satellite images, including pre-processing, LULC classification by using Landsat satellite images, and accuracy assessment;
3. Process the input data for the RUSLE model in estimating soil erosion rate;
4. Simulate the coupled RUSLE-SDR model for predicting sediment yield, and validation with the measured sediment data;

5. Perform runoff estimation and analysis of the relationship between surface runoff and landslide occurrences; and
6. Propose land use scenarios for reducing soil erosion, sediment yield, and runoff to contribute hazard mitigation within the study basin.

Research on assessment of soil erosion, runoff and establishment
of land use scenarios for soil-water conservation at Zhuoshui river basin

Chapter 3 Progress and work package

3.1 Gantt chart

No	Items	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
I	Collect Data											
1	Digital elevation map											
2	Soil map											
3	Land use, land cover maps											
4	Rainfall at meteorological stations											
5	Observed sediment at gauge stations											
6	Runoff and water discharge at gauge stations											
7	Landsat satellite images											
II	Process the temporal satellite images											
1	Pre-processing satellite images											
2	LULC classification from Landsat satellite images											
3	Accuracy assessment											
4	Analyze LULC changes											
III	Process the input data for the RUSLE model, sediment yield estimation											
1	Crop management factor											
2	Rainfall erosivity factor											
3	Soil erodibility factor											
4	Slope length and slope steepness factor											
5	Support practice factor											
IV	Simulate the RUSLE model and sediment yield											
1	Simulate the RUSLE model											
2	Predict the sediment yield											

Research on assessment of soil erosion, runoff and establishment
of land use scenarios for soil-water conservation at Zhuoshui river basin

3	Validate predicted sediment yield with the observed sediment data											
V	Perform runoff estimation and landslide inventory											
1	Runoff estimation by using SCS-CN model											
2	Validate runoff calculation											
3	Landslide inventory using satellite images or other sources											
4	Analysis of the relationship between runoff and landslide occurrences											
VI	Establish land use scenarios											
1	Slopeland capability classification											
2	Establish land use scenarios											
VII	Finalize the project											
1	Write the final reports											
2	Submit the final result											

3.2 Work package

Work package No.1:

Analyzing Land use/land cover change from 2005 to 2019

3.2.1 Data of Work Package 1

3.2.1.1 Satellite images

In this project, for the land use/land cover (LULC) classification task, we principally used the Landsat satellite images (Landsat 5 TM, Landsat 8 OLI TIRS). Landsat image with a medium spatial and high temporal resolution (30-m spatial resolution and 16-day temporal resolution) is intensively collected for spatio-temporal monitoring of LULC dynamics. Thus, these satellite images can be employed to analyze the LULC change from 2005 to 2019. It is suitable for the temporal analysis of the region covered by clouds frequently.

To reduce the seasonal and cloud impacts on the classification results, we primarily focus on processing the images acquired from January to April (dry season). However, in some cases, because of clouds, we use some images from October to December of the previous year (Tables 3, 4, and 5).

In order to cover the whole study area, 4 scenes of Landsat images are needed (Scene 1: Path = 118, Row = 43, Scene 2: Path = 118, Row = 44, Scene 3: Path = 117, Row = 43, Scene 4: Path = 117, Row = 44) (Fig. 5).

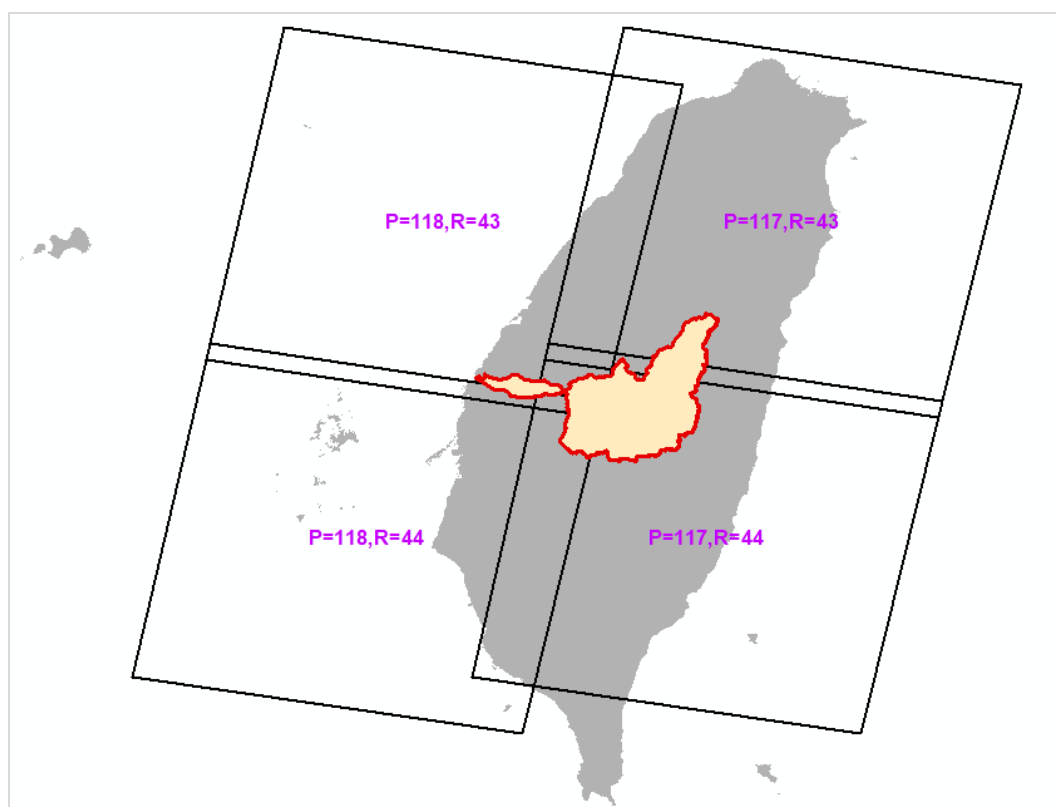


Figure 5. Scenes of Landsat image covering the study area.

Table 3. Landsat 8 images used in this project (2019).

Specifications	Path/Row			
	118/43	118/44	117/43	117/44
Date	2019/01/18	2019/01/18	2019/01/11	2019/01/11
	2019/02/03	2019/02/03	2019/01/27	2019/02/12
	2019/04/08	2019/02/19	2019/02/12	2019/02/28
	2019/04/24	2019/04/08	2019/02/28	2019/03/16
		2019/04/24	2019/04/17	2019/04/01
				2019/04/17
Level	Level-1			
Band	Blue, Green, Red, NIR, SWIR-1, SWIR-2, and Thermal			
Resolution	30 m			
Bit depth	16 bits			

Table 4. Landsat 5 images used in this project (2011).

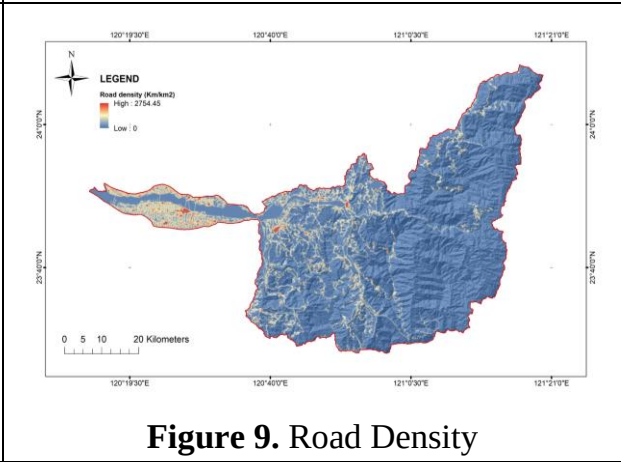
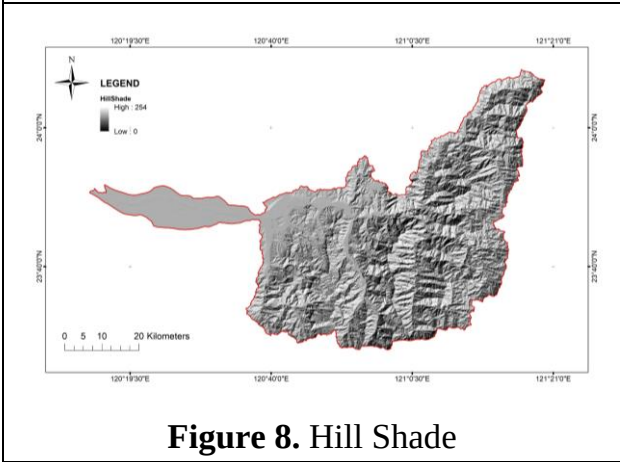
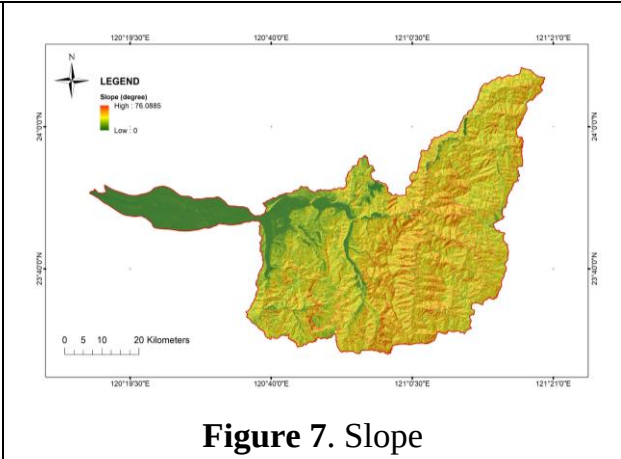
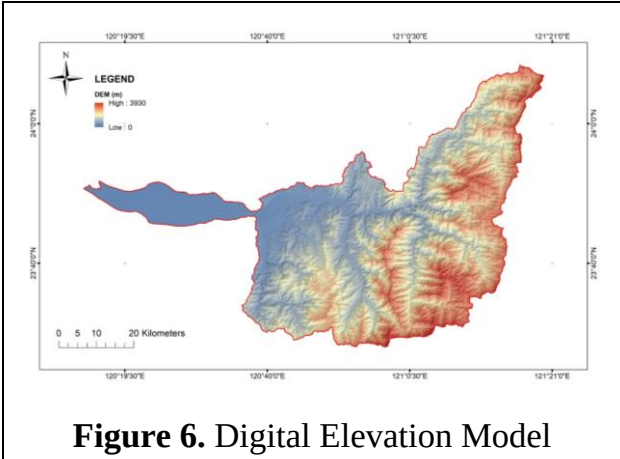
Specifications	Path/Row			
	118/43	118/44	117/43	117/44
Date	2011/03/01	2011/01/28	2011/01/05	2011/01/05
	2011/04/02	2011/02/13	2011/02/06	2011/02/22
	2011/04/18	2011/03/01	2011/02/22	2011/02/06
		2011/04/02	2011/04/11	2011/04/11
		2011/04/18	2011/04/27	2011/04/27
Level	Level-1			
Band	Blue, Green, Red, NIR, SWIR-1, SWIR-2, and Thermal			
Resolution	30 m			
Bit depth	8 bits			

Table 5. Landsat 5 images used in this project (2005).

Specifications	Path/Row			
	118/43	118/44	117/43	117/44
Date	2005/02/12	2005/01/11	2005/01/20	2005/01/20
	2005/03/16	2005/01/27	2005/02/05	2005/02/05
	2004/12/10	2005/02/12	2005/03/09	2005/03/09
	2004/11/08	2005/03/16	2005/03/25	2005/03/25
		2005/04/01	2005/04/10	2005/04/10
		2005/04/17		
Level	Level-1			
Band	Blue, Green, Red, NIR, SWIR-1, SWIR-2, and Thermal			
Resolution	30 m			
Bit depth	8bits			

3.2.1.2 Ancillary data

For better classification results, in this study, we used some types of additional data, such as Digital Elevation Model (DEM), slope, hill shade, aspect, and road networks (Figs. 6-9). The ancillary data can be used to create a more complicated algorithm for classification and reduce the overfitting problems, thus obtaining higher accuracy.



3.2.2 Methodology of Work Package 1

3.2.2.1 Flowchart

The flowchart for LULC classification was used in this study (Figure 10):

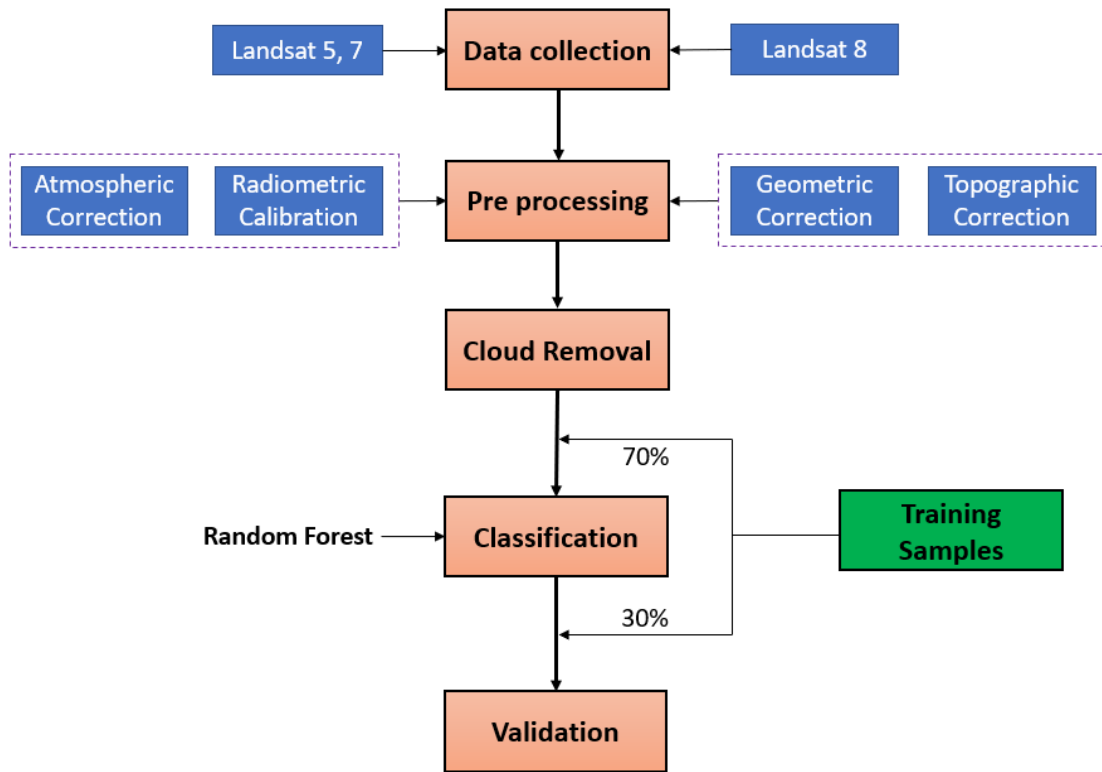


Figure 10. Flowchart of LULC classification.

3.2.2.2 Pre-processing and Cloud Removal

After collecting the Landsat 5 images, i.e., 8 images of the study area, the images were processed through two major steps. The first step is to perform geometrical rectification, radiometric calibration, atmospheric correction, and topographic correction. After that, the images underwent cloud detection and removal to create the cloud-free Landsat images for the study area (Fig.11). Some indices were also calculated to support the sample selection step (Fig.12).

Research on assessment of soil erosion, runoff and establishment
of land use scenarios for soil-water conservation at Zhuoshui river basin

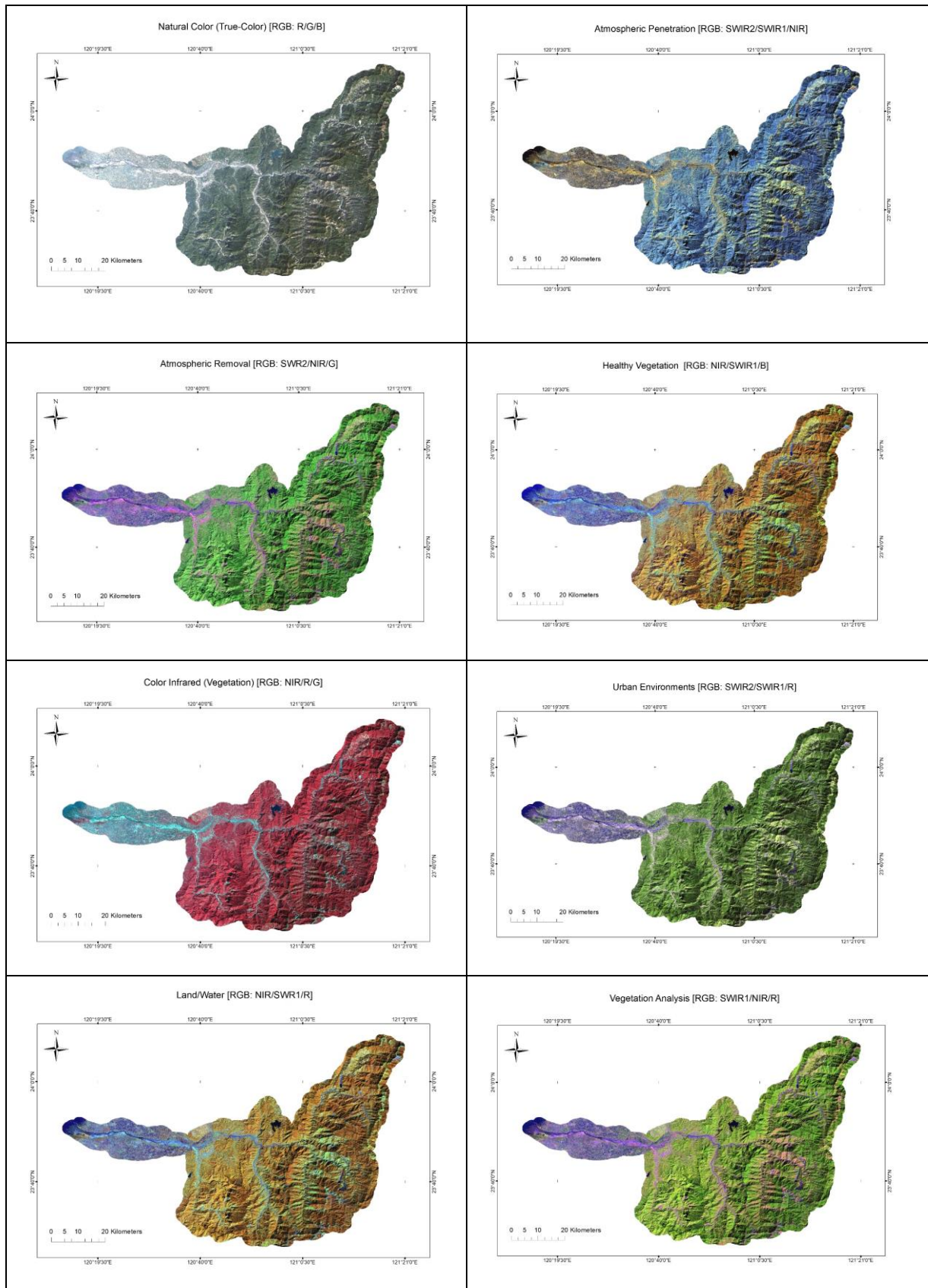


Figure 11. Band combination for better visualization.

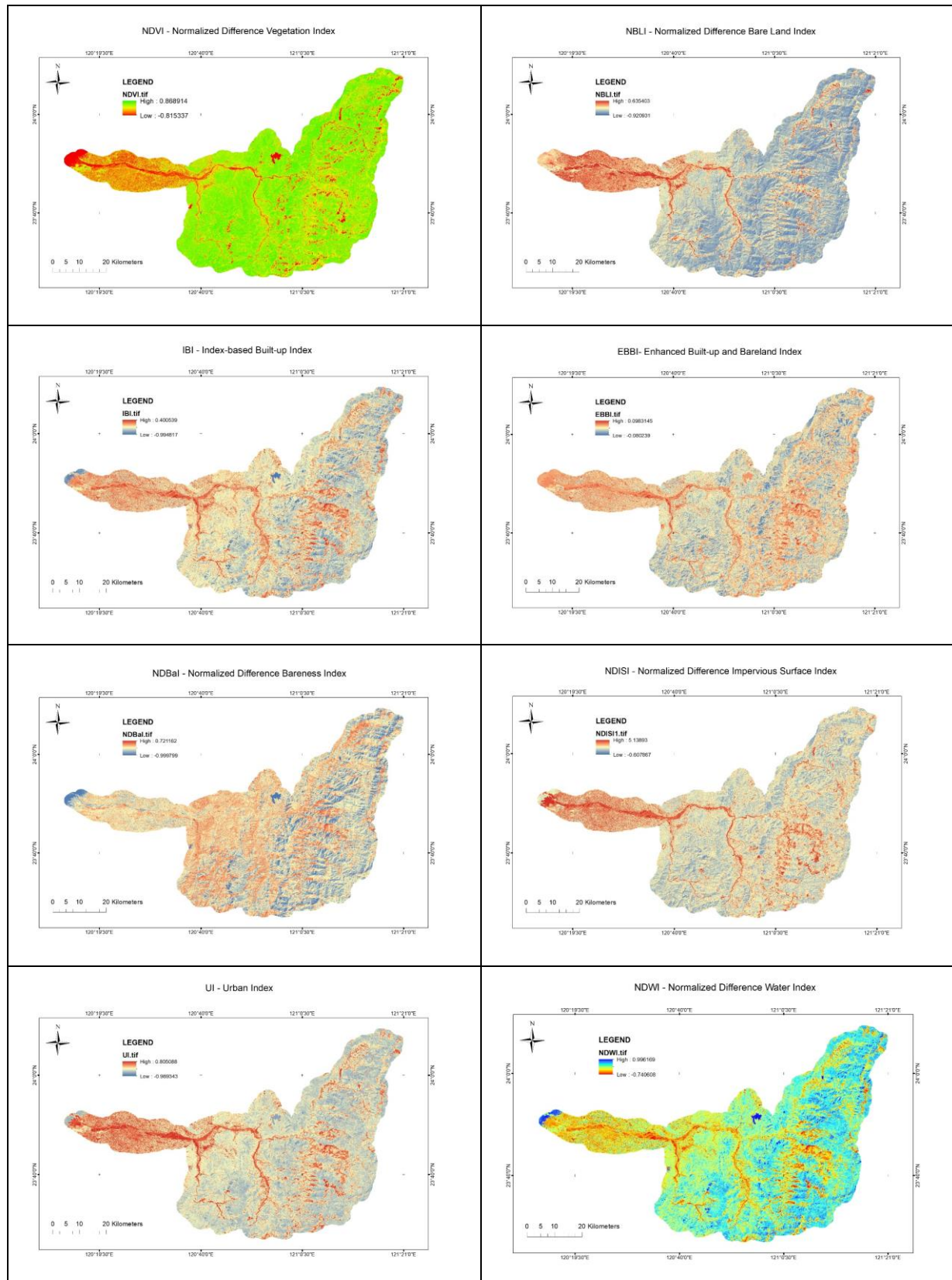


Figure 12. Indices for aiding sample selection.

3.2.2.3 Sampling

In the study area, the dominant land cover types include forest, built-up land, bare land, agricultural land, and water body. In practice, the land cover types were divided into smaller classes for better matching the spectral profile, and then combine them to create five main classes. In addition, we used the combination of different band composites, indices, and high-resolution images from Google Earth to support the sample selection in the LULC classification task. The distribution of samples for the years 2005, 2011, and 2019 was depicted in Figures 13, 14, and 15, respectively.

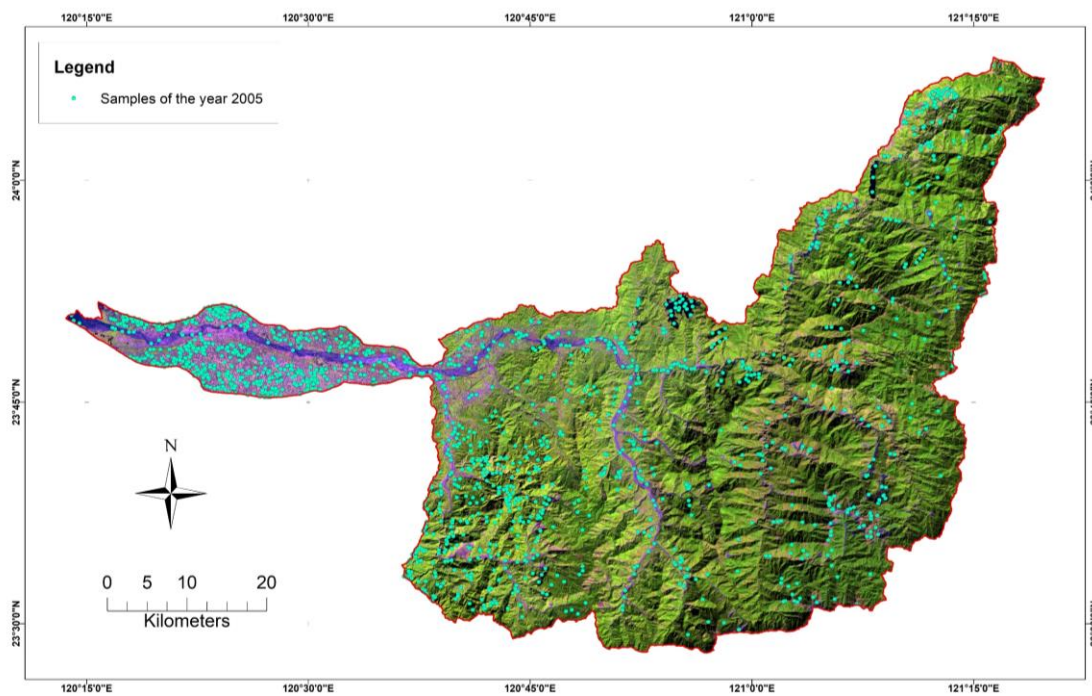


Figure 13. Sample distribution of the year 2005.

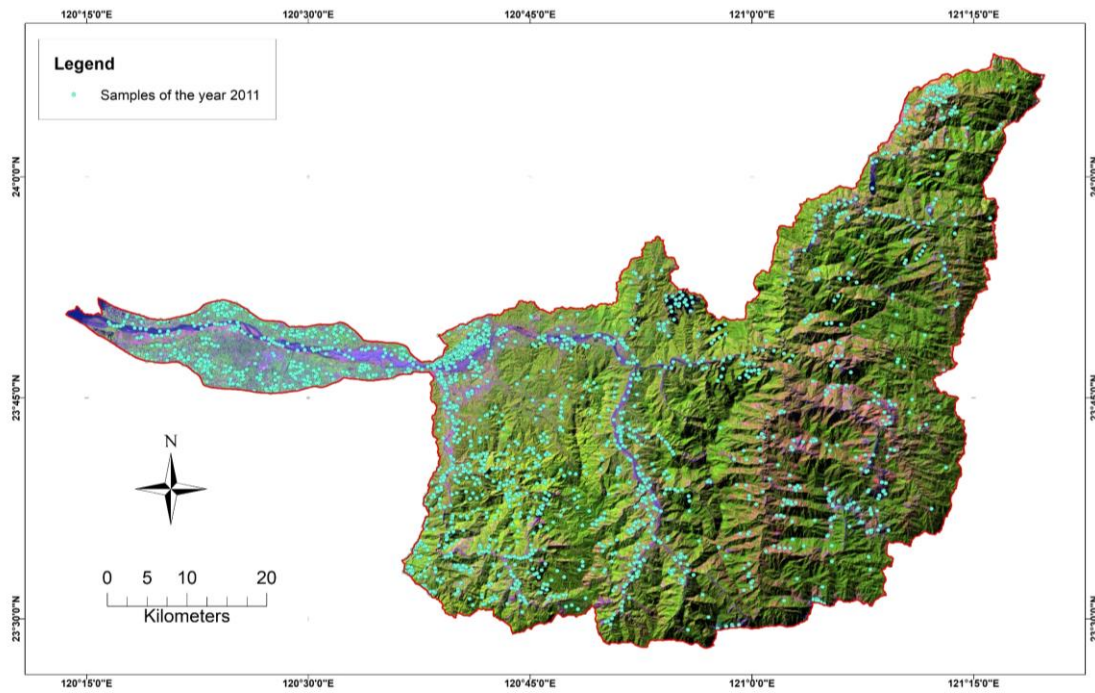


Figure 14. Sample distribution of the year 2011.

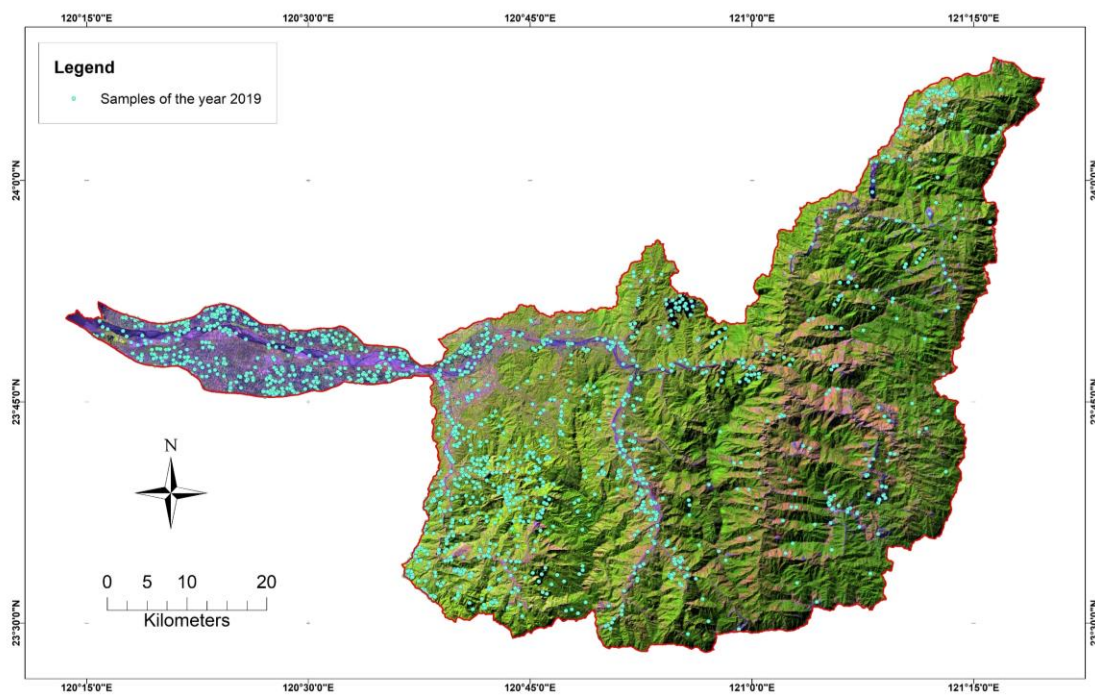


Figure 15. Sample distribution of the year 2019.

3.2.2.4 Algorithm for LULC classification

The algorithm of LULC classification employed in this project is the Random Forest classifier. It is an improvement of decision tree algorithm that has a main drawback of overfitting training data. Thus, Random Forest is an alternative way to solve this problem. Basically, the Random Forest is a group of decision trees with small difference between them, and classification results are decided by using a majority vote after employing the boots trapped sample method on the training data [20].

The Random Forest algorithm has two types of parameters. The first one is the parameters of a model that can be learned by minimizing some loss functions in the training process. The second one is the hyperparameters, which must be chosen before the beginning of training process. Two of the most important hyperparameters of the algorithm are n-estimators (tree number) and max-depth (model depth). In this study, these optimal hyperparameters were determined by using the validation curves (n-estimators = 50, max-depth = 20) (Figures 16 and 17). These hyperparameters then were used by the Random Forest algorithm to identify the LULC types of the study site.

The evaluation stage obtained the samples from the image itself and from high-resolution image of Google Earth to examine the accuracy of classification results. In this study, we splitted the samples into training part (70%) and testing part (30%). After the model was trained with training data, the testing data were used for evaluating the model performance. Accuracy assessment was conducted by using the confusion matrix and Kappa coefficient.

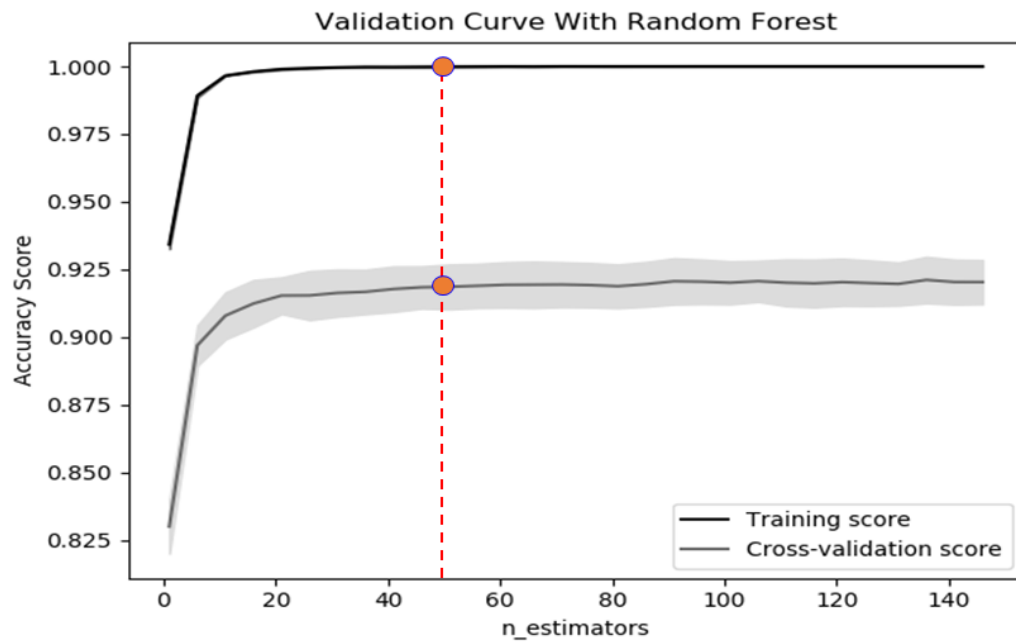


Figure 16. Finding the number of trees (n-estimators).

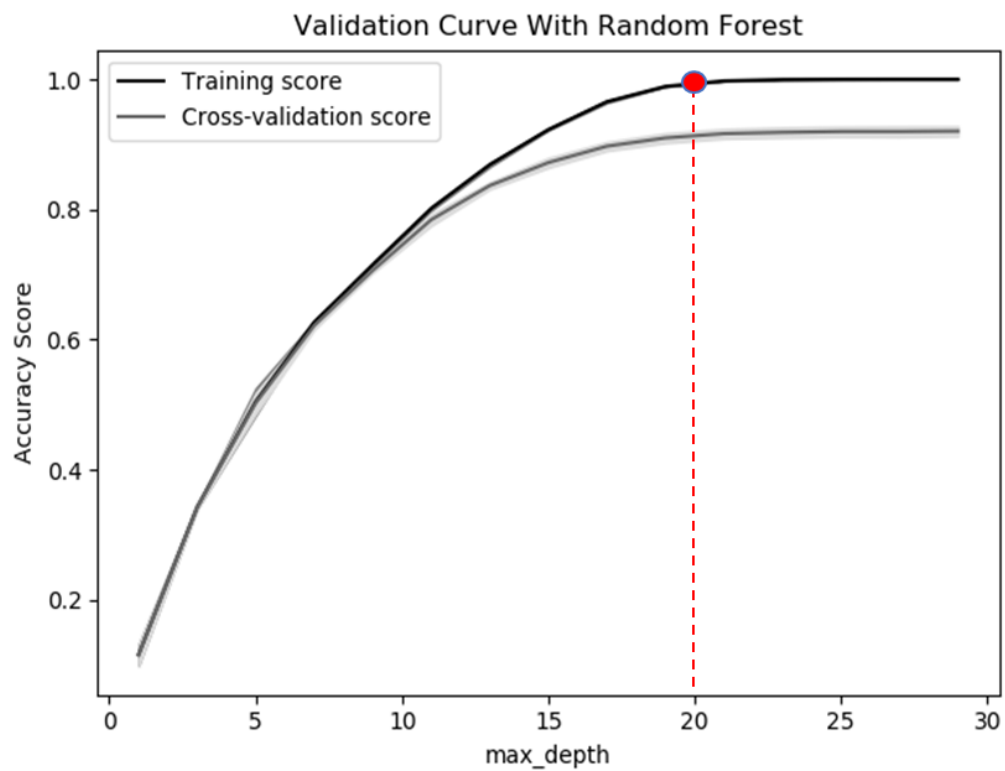


Figure 17. Finding the max-depth hyperparameter.

3.2.3 Result of Work Package 1

3.2.3.1 LULC classification

Results of mapping the LULC classification for the three years of interest (2005, 2011 and 2019) can be seen from Figures 18, 19, and 20, respectively. From these figures, it reveals that the forest accounts a large proportion of the study area; and it locates in the mountainous area at high elevation with steep slope. For the forest, it is widely distributed on the East-West parts and stable through the time period of study. Bare land is commonly located in the mountainous area in the East of the study area, while water body is seen along the river and some lakes. As for the urban area, it is mostly situated on the plain area with slight slope and along the roads. For the agriculture land, most of the land is located on the flat plain, and some areas are distributed on the mountainous area.

The results of LULC classification for the years 2005, 2011 and 2019 show satisfactory performance. The overall accuracy is rather high with correlations of 0.91%, 0.93% and 0.90%, for 2005, 2011, and 2019, respectively. Additionally, the Kappa index was also high with values of 0.91, 0.92 and 0.90 for three different years 2005, 2011 and 2019, respectively.

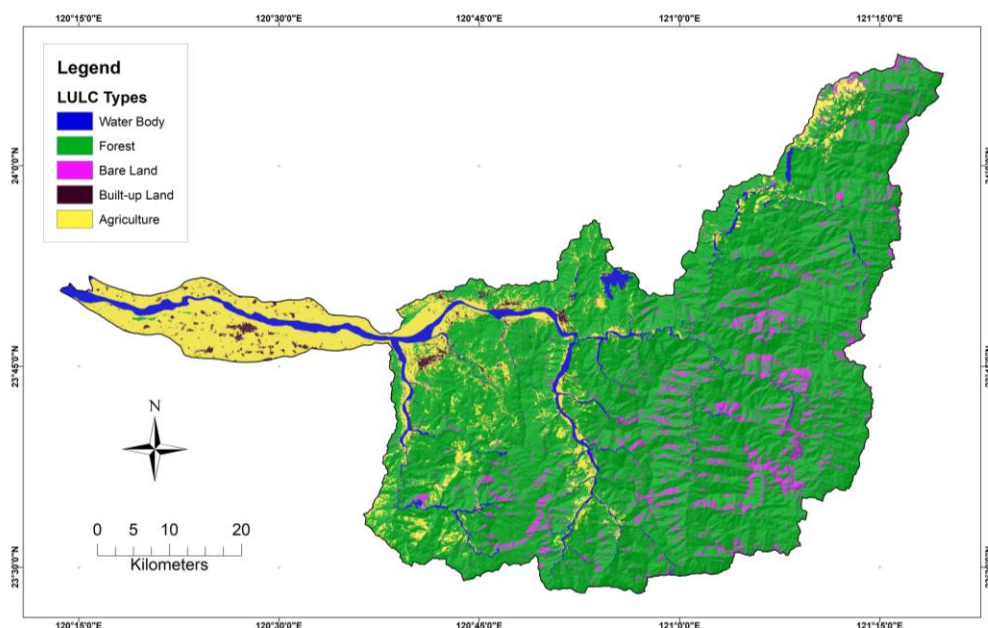


Figure 18. LULC map of the year 2005.

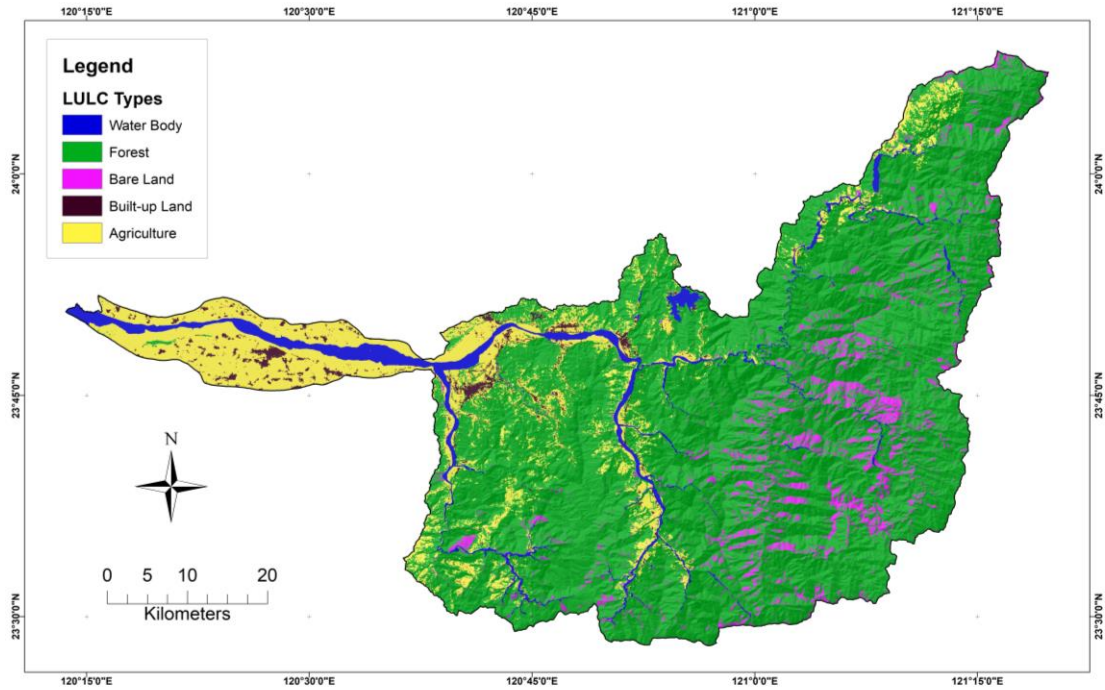


Figure 19. LULC map of the year 2011.

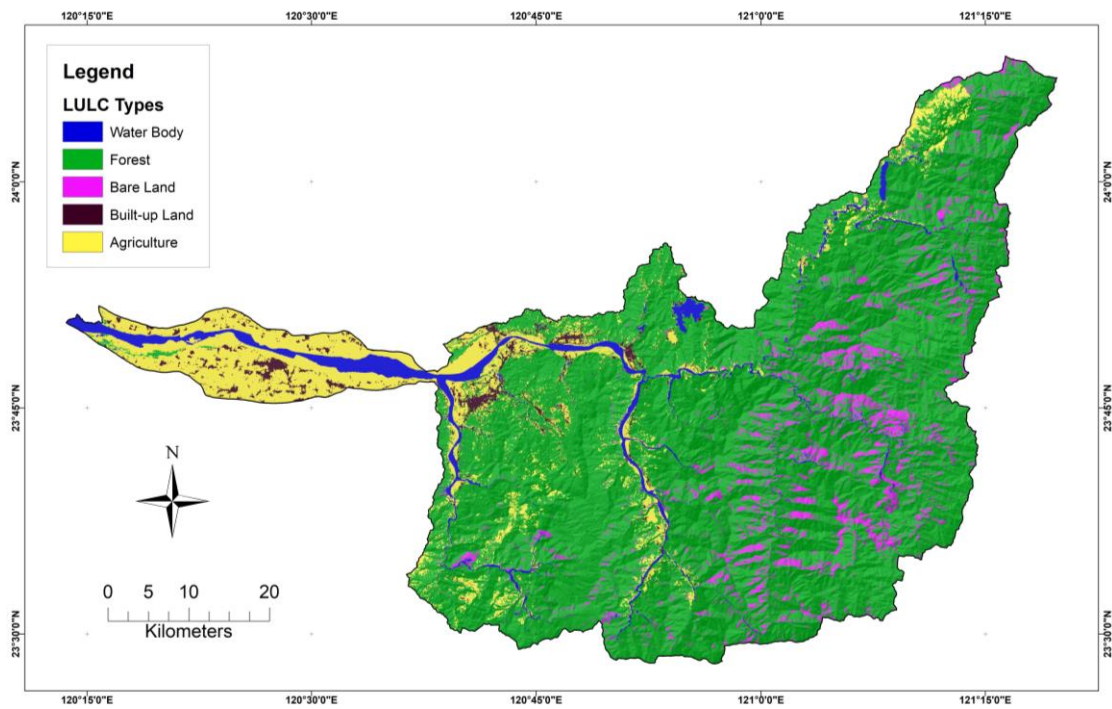


Figure 20. LULC map of the year 2019.

3.2.3.2 LULC Change

In this project, to investigate LULC dynamics, the post-classification comparison method is employed for change detection. This method is capable to provide a matrix of change information, which provides the users a better view of LULC change. Another advantage of this method when applying for multi-temporal satellite images is the reduction of atmospheric and environmental influences. However, to carry out the classification method, a variety of high-quality training samples are required to classify the LULC accurately. In addition, due to the difficulty in collecting the high-quantity training sample data, the classification results of historical satellite images are often less accurate than the new ones, thus negatively affecting the change detection results. In this study, the areas of LULC changes through the 2005-2019 period are stated in Table 6; and the transfer matrices to determine the 2005-2011 land-cover changes and 2011-2019 land-cover changes are shown in Table 7 and Table 8, respectively.

Table 6. Land-cover transfer matrix from 2005 to 2019.

LULC Types	2005 (ha)	2011 (ha)	2019 (ha)	2005-2019 Change Ratio (%)
Water Body	12733.65	13593.69	12455.28	-2.23
Forest	239243.00	237657.96	240571.98	0.55
Bare Land	20558.34	18491.49	21053.25	2.35
Built-up Land	3604.41	5054.94	6175.17	41.63
Agriculture	40285.90	41626.26	36168.66	-11.38

Table 6 summarizes the areas of water, built-up land, bare land, and vegetation in 2005, 2011, and 2019. Approximately 76% of the total land is covered by forest, 4% by water, 6% by bare land, 12.5 % by agricultural land, and only 1.5% by built-up land. While forest accounts for a large portion of the study area, its coverage is quite stable from 2005 to 2019 (Figure 20). In contrast, the built-up land is increased constantly from 3640.41 ha in 2005 to 5054.94 ha in 2011, and 6175.17 ha in 2019. The built-up land is mainly converted from the agriculture land. The area of bare land is slightly

decreased from 20558.34 ha in 2005 to 18491.49 ha in 2011, and increased to 21053.25 ha in 2019, resulting in a total increase by 2.35% from 2005 to 2019. In contrast, the area covered by agriculture shows a decrease from 40285.90 ha (2005) to 36168.66 ha (2019).

Table 7. Land-cover transfer matrix from 2005 to 2011.

2011 2005	Water Body	Forest	Bare land	Built-up land	Agricultural land	Total (ha)
Water Body	10223.73	677.16	429.85	147.42	1265.49	12733.65
Forest	792.54	225831.51	6142.59	160.47	6315.93	239243.00
Bare land	306.18	7967.34	11767.95	40.23	476.64	20558.34
Built-up land	108.45	72.45	15.30	2943.90	464.31	3604.41
Agricultural land	2162.79	3109.50	145.80	1762.92	33103.89	40284.90
Total (ha)	13593.69	237657.96	18491.49	5054.94	41626.26	316424.30

Table 8. Land-cover transfer matrix from 2011 to 2019.

2019 2011	Water Body	Forest	Bare land	Built-up land	Agricultural land	Total (ha)
Water Body	10657.89	954.36	379.08	149.85	1452.51	13593.69
Forest	334.26	228312.81	6399.90	234.63	2376.36	237658.00
Bare land	549.09	3626.10	14115.96	58.50	141.84	18491.49
Built-up land	94.95	244.98	10.71	4019.76	684.54	5054.94
Agricultural land	819.09	7433.73	147.60	1712.43	31513.41	41626.26
Total (ha)	12455.28	240571.98	21053.25	6175.17	36168.66	316424.30

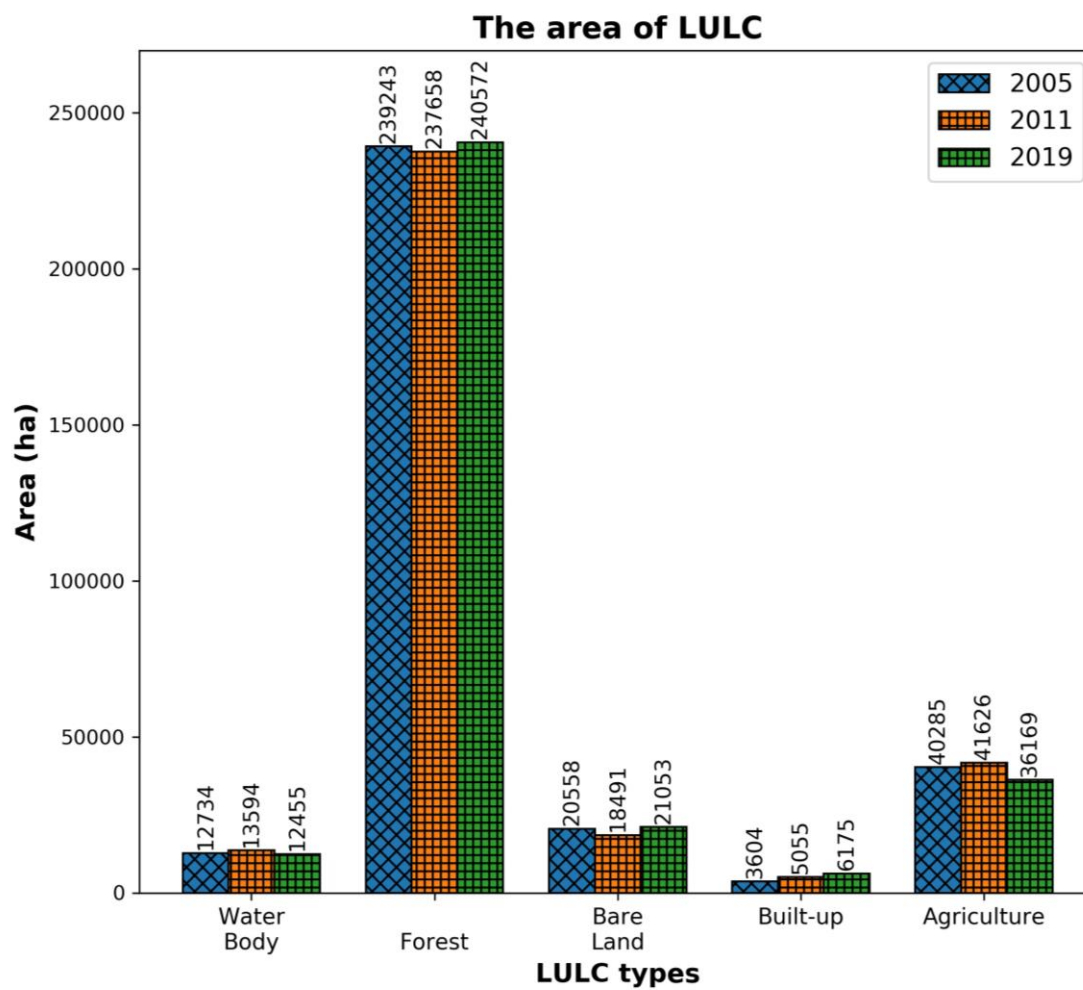


Figure 21. The area of LULC for the years 2005, 2011 and 2019.

Work package No.2:

Estimation of soil erosion and sediment yield by using the RUSLE (Revised Universal Soil Loss Equation) and sediment delivery ratio

3.2.4 Introduction of Work Package 2

Nowadays, sustainable development has been receiving more attention worldwide than before to ensure the balance between the socio-economic development and environmental protection. In the tropical regions, soil erosion is considered as the most threatening risk for soil conservation and ecosystem services due to the removal of native vegetation for agricultural expansion without any application of conservation practices. Consequently, it causes economic and social losses, and accelerates environmental issues. Soil erosion process results in the losses at on- and off-site. It removes arable soil depth and leads to soil fertility decline, while it causes sedimentation deposition and eutrophication at downstreams. As a result, it reduces the capacity of rivers and drainages and increases flooding [21]. In the agricultural aspect, soil erosion threatens sustainable food production, particularly in sloping land, shallow soils, insufficient and absence of soil erosion control measures.

Until now, there is an array of soil erosion models developed by various organizations and researchers, including empirical models, physical-based models, etc. Currently, soil erosion prediction has been carried out by a wide range of models, such as the Agricultural Non-Point Source Pollution model (AGNPS), the Water Erosion Prediction Project (WEPP), the Erosion Productivity Impact Calculator (EPIC), the Areal Nonpoint Source Watershed Environment Response Simulation (ANSWERS), Soil and Water Assessment Tool (SWAT), etc.[22], but Universal Soil Loss Equation (USLE) is still the most widely used empirical model [23]. It was originally proposed by Wischmeier and Smith [24] and then revised by Renard et al. [25] to predict the annual soil loss rate by inter-rill and rill erosion process.

Currently, the USLE model is the standard model for the soil loss prediction mentioned in the Soil and Water Technical Regulations by Taiwan's Council of Agriculture [22]. This model uses six parameters that affect soil erosion process by

water including climate, land use/land cover, soil properties, topographic condition, and conservation practices. Because of its drawbacks in the simplicity and standardized methodology, the USLE has been revised to improve its performance with respect to the additional use of digital elevation model (DEM) and redeveloping cover management (C factor).

In this study, the six factors of the RUSLE model extracted from various studies by using the GIS and RS techniques, especially with some factors referred from the antecedent studies in Taiwan. These input parameters have further been incorporated into the Soil and Water Conservation Bureau's Handbook for designing the soil and water conservation facilities in controlling the sediment volume [26]. The objective of this part is to perform spatio-temporal mapping of soil erosion rate by using the RUSLE model at the Zhuoshui River Basin.

After the RUSLE performance, this study combines the long-term average annual soil erosion from the RUSLE model and empirical SDR equations developed in Taiwan to estimate the SY for each sub-basin. The predicted SY at each sub-basin then will be validated with the measured sediment at each gauge station corresponding to its outlet.

3.2.5 *Material of Work Package 2*

To stimulate soil erosion rate, the RUSLE model was employed to predict long-term annual soil erosion with the support of GIS and remote sensing techniques. To achieve this purpose, the data were collected from various sources as addressed below:

- Digital Elevation Model (DEM) with the 30-m resolution was download from the USGS website;
- Long-term annual rainfall was collected from 49 meteorological stations within and surrounding the Zhuoshui River Basin;
- Soil information obtained from Taiwan Agricultural Research Institute Council of Agriculture, Executive Yuan; and
- Annual NDVI was extracted from Landsat images of the years 2005, 2011, and

2019 via Google Earth Engine for further analysis.

- Measured sediment data were obtained from Water Resource Agency (WRA) from 2005 to 2018.

To quantify the input of the RUSLE model, this study assembled various GIS software packages in spatial data processing, such as ArcGIS, SAGA, QGIS.

3.2.6 Methodology of Work Package 2

3.2.6.1 Estimating the inputs for the RUSLE modeling

The RUSLE (Revised Universal Soil Loss Equation) was originally developed by Wischmeier and Smith [24] and then modified by Renard et al. [25].

$$A = R * K * L * S * C * P \quad (1)$$

where,

A = average soil loss rate ($t \text{ ha}^{-1} \text{ year}^{-1}$)

R = rainfall erosivity ($\text{MJ} \cdot \text{mm} \text{ ha}^{-1} \text{ h}^{-1} \text{ yr}^{-1}$)

K = soil erodibility ($\text{ton} \cdot \text{h} \text{ MJ}^{-1} \text{ mm}^{-1}$)

L = slope length

S = slope steepness

C = cover and management

P = conservation practices

a. Rainfall Erosivity (R factor)

This parameter shows the energy of precipitation that can detach and transport soil particles from the surface to the other sites. It depends on the amount and magnitude of rainfall. Originally, it can be calculated by the equation proposed by Wischmeier et al. [27]. The measurement of annual R factor needs to collect the mean annual value of EI_{30} that is a function of storm kinetic energy (E) and maximum 30 min intensity (I_{30}) obtained from detailed and long-term records [28]. Because of the detailed data acquisition for the standard-R equation of rainfall erosivity is unavailable in some studied areas, some authors developed alternative formulas for a certain

region, which only use monthly or annual rainfall data. El-Swaify et al. [28], for example, used annual rainfall for retrieving the R factor and it is extensively applied in Thailand, Philippines, and Sri Lanka.

To estimate the R value, this study chose the equation proposed by Lu et al. [16] for Nantou nearby the Zhuoshui River Basin:

$$R = 17.02 * 0.020653 * P^{1.35072} \quad (2)$$

where R is rainfall erosivity ($\text{MJ} \cdot \text{mm} \cdot \text{ha}^{-1} \cdot \text{h}^{-1} \cdot \text{yr}^{-1}$); and P is the annual average rainfall in mm.

The long-term rainfall data from 49 meteorological stations was collected with their geographical locations. Currently, there is a wide range of interpolation techniques to delineate the spatial distribution of rainfall. Due to the influence of topographical conditions on rainfall in the mountainous areas, this study analyzed the relationship between average annual rainfall at 49 stations with elevation by using linear regression. The result showed a close relationship between rainfall and elevation with an R coefficient of 0.6. Thus, we attempted to use the Co-Kriging method by using DEM as an external factor to improve the rainfall distribution mapping. This method produced a spatial rainfall map with a root mean square error (RMSE) value of 371.88 (mm).

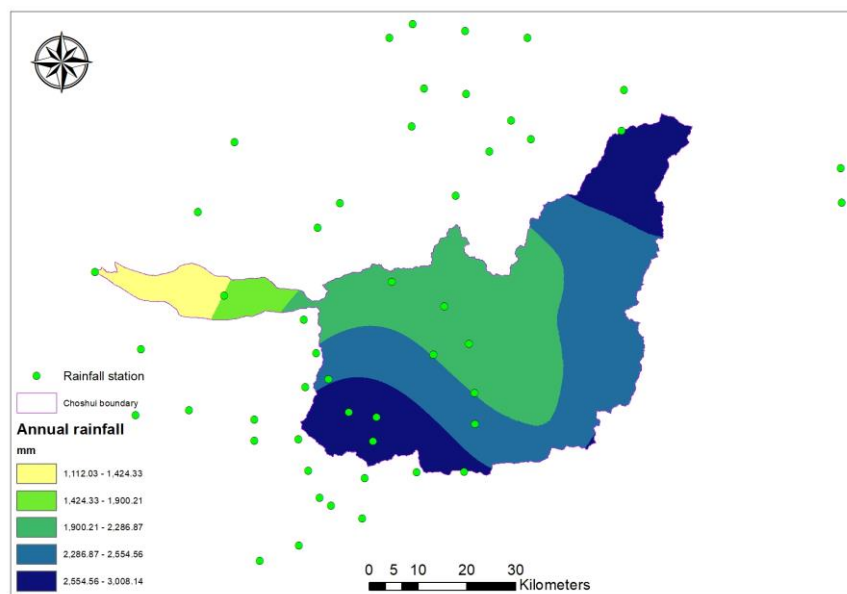


Figure 22. Annual rainfall map & rainfall stations.

b. Soil erodibility (K factor)

This parameter expresses the ability of soil to resist the force of rainfall and runoff. Wischmeier and Smith (1978) and Renard et al. (1997) use the K equation for the RUSLE that requires soil texture, structure, organic matter content, soil permeability, and infiltration. However, these parameters might be not available or match with soil category [28]. Thus, some alternative methods were produced to estimate soil erodibility with less required soil information than the original formula. For example, Williams and Renard [29] used sand, silt, clay, and organic content, whereas David [30] used one more parameter, pH value, and El-Swaify and Dangler [31] just only used textural information and base saturation.

In this study, the K factor used the Soil Index (KI) following Taiwanese soil types and from its relation to the K value of the USLE model. The K factor can be converted from KI by using equation [16]:

$$KI = \text{Int}(200K) + 1 \quad (3)$$

Table 9. K value extracted from KI value based on Taiwanese soil types (Adapted from Chen et al. [16]).

Soil types	KI value	K
Diluvial Material Yellow Soils	10	0.045
Diluvium Red Soils	7	0.030
Metamorphic Rock Pale Colluvial Soils	8	0.035
Miscellaneous Lands	11	0.050
Precipitous Areas	8	0.035
Sandstone-Shale Darkish Colluvial Soils	7	0.030
Sandstone-Shale Lithosols	6	0.025
Sandstone-Shale Order Alluvial Soils	12	0.055
Sandstone-Shale Pale Colluvial Soils	14	0.065
Sandstone-Shale Yellow Soils	7	0.030
Sandstone-Shale-Slate Calcareous Alluvial Soils	10	0.045
Sandstone-Shale-Slate Non-Calcareous Alluvial Soils	13	0.060
Slate Calcareous Alluvial Soils	3	0.010
Slate Calcareous Older Alluvial Soils	11	0.050
Slate Non-Calcareous Alluvial Soils	11	0.050

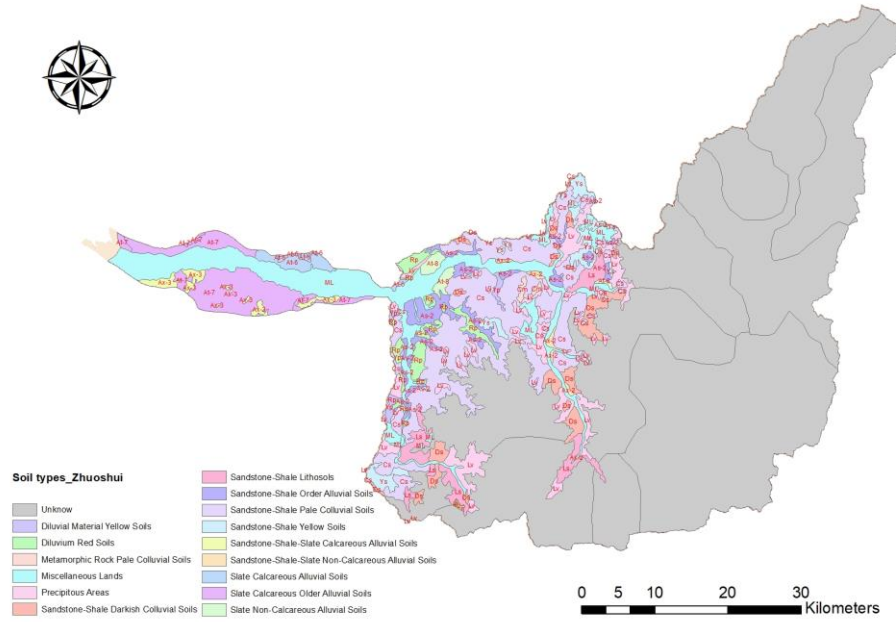


Figure 23. Taiwanese soil types.

c. Topographic factor (LS factor)

This factor includes slope length (L) and steepness (S) that strongly affect soil loss and describe the effect of topology on soil erosion. This study calculated L – slope length from Desmet and Gover [32]:

$$L_{ij-in} = [(A_{ij-in} + D^2)^{m+1} - (A_{ij-in})^{m+1}] / [D^{m+2} * x_{ij}^m * 22.13^m] \quad (4)$$

where A_{ij-in} is the contributing area at the inlet of the grid cell (i,j) measured in m^2 ; and D is the grid cell size (meters);

$$x_{ij} = \sin a_{ij} + \cos a_{ij};$$

a_{ij} is the aspect direction of the grid cell (i,j); and

$$m \text{ is related to the ratio } \beta \text{ of the rill to interill erosion: } m = \beta / (\beta + 1) \quad (5)$$

where,

$$\beta = (\sin \theta / 0.0896) / [(0.56 + 3 * (\sin \theta)^{0.8})] \quad (6)$$

θ is the slope angle in degrees;

m ranges between 0 and 1; and

S factor is calculated following Zevenbergen and Thorne [33]:

$$G_{ij} = \sqrt{G_x^2 + G_y^2} \quad (7)$$

where G_x is gradient in the x-direction (m/m) and G_y is gradient in the y-direction (m/m).

Desmet and Gover [34] proved that this LS factor is appropriate for modeling the soil erosion at landscape-scale and can represent complex topography.

To stimulate the LS factor, the DEM at 30 m that is the main input used to extract the LS value was put into the SAGA software with the support of the terrain analysis tool.

d. Cover and Management (C factor)

It is an important factor that strongly influences and controls the soil erosion process. It represents the ability of vegetation to protect the soil surface from raindrop and runoff attacks. Currently, the C factor can be calculated from various methods, such as field measurement of ground cover, look-up table from antecedent studies. In the RUSLE, the standard calculation of the C factor is a function of 5 sub-factors, including prior land use (PLU), canopy cover (CC), surface cover (SC), surface roughness (SR), and soil moisture (SM) [9]. With such detailed data information, the soil erosion modeling is only feasible at micro-scale, such as plot, field, or farming, while at the catchment or larger scale, most of the input data for the C sub-factors became infeasible or impossible to quantify [9]. In addition, the look-up table to assign the C factor is a simple method, but it reveals some drawbacks due to the temporal variations in cover and crop over a large region [28]. With the advances of remote sensing (RS) in terms of temporal and spatial coverage, the C factor based on RS has been developed and popularly applied to study on soil erosion at a macro scale.

This study obtained the C value from NDVI-based transformation. This approach is intensively used to extract the C factor of the RUSLE model instead of land use/land cover-based method. Normalized Different Vegetation Index (NDVI) represents green healthy vegetation by calculation of the spectral reflectance difference between red and near-infrared bands of the satellite image and ranges from -1 to +1 [35]:

$$NDVI = (NIR - RED)/(NIR + RED) \quad (8)$$

where NIR is the surface spectral reflectance in the near-infrared band and RED is the surface spectral reflectance in the red band.

The C factor is estimated by using NDVI transformation proposed by various studies, such as Durigon et al. [36] and van der Knijff et al. [37]. The equation proposed by Lin et al. [22] based on the verification of several watersheds in Taiwan was used in this study:

$$C = [(1 - NDVI)/2]^{1 + NDVI} \quad (9)$$

Google Earth Engine (GEE) was used to acquire Landsat time-series data of the years 2005, 2011 and 2019. Pre-processing was required for further analysis. The removal of clouds and cloud shadows were firstly conducted by using the CFMask algorithm. Secondly, the topographic illumination correction was performed by applying a physical method proposed by Dymond and Shepherd [38]. Finally, the yearly mean Landsat data were obtained for the years of concern and exported as three single cloud-free images. After that, NDVI-based transformation in Equation 9 was utilized to calculate the mean C value of the three years.

e. Conservation practice (P)

It represents the effects of controlled measurements that will reduce the rate of the amount of runoff and raindrop that strike on the soil surface. The common support practices are contour farming, terracing, strip cropping, and grassed waterways [39]. The lower the P value, the more effectively the support practice promotes the deposition of soil particles [9].

Within the RUSLE, a list of the P values corresponding to a wide range of support practice conditions mainly comes from experiment data at plots or field scale. Therefore, while transferring the P factor from a field scale to a large scale based on GIS-based modeling, it is considered as the least reliable of the RUSLE factors because of the lack of spatial information [9]. To overcome this limitation, this study applied an equation developed by Wener [39] that shows the linear relationship between slope (S in percentage) and the amount of conservation practice (P):

$$P = 0.2 + 0.03 * S \quad (10)$$

where P is the amount of conservation practice; and S is the percentage of slope.

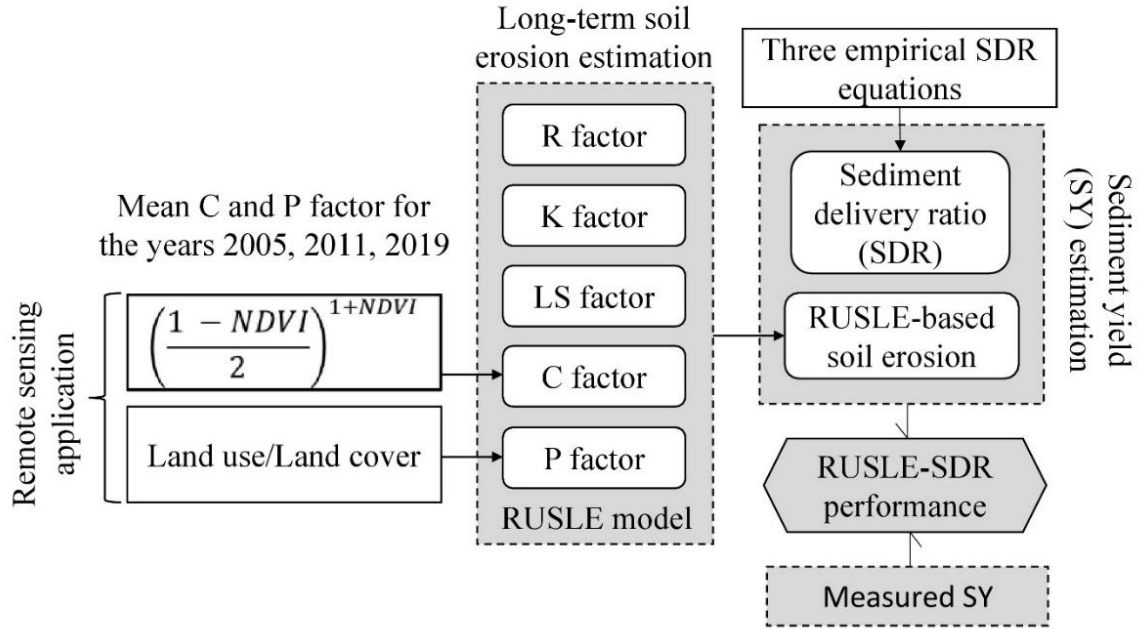


Figure 24. The flowchart of summarizing steps for soil erosion and sediment yield assessment in the study area.

3.2.6.2. Sediment delivery ratio and sediment yield estimation

The SDR is defined as the proportion of gross erosion that is expected to travel to the outlet of a given catchment area [40]. It is influenced by various environmental variables, such as rainfall, vegetation, topography, and soil properties and their complicated interactions [41]. The straightforward way of determining the sediment yield in a watershed is a long-term, direct measurement of the suspended load and bed load at a specific outlet cross section of a watershed. However, it takes enormous time and efforts to do so and the reasonability and correctness of direct measurements are often questioned due to the concern about observation instruments and testing [16]. Due to the complexity in the mechanism of basin sediment transport, the physically-based distributed models are still rarely seen [42]. Thus, the empirical SDR developed for a given watershed is widely used in estimating SDR.

Currently, the RUSLE model cannot be directly used to predict the SY because a part of the eroded sediment may be deposited before traveling to catchment outlet [43]. Moreover, the RUSLE does not consider gully erosion, river channel erosion or sediment deposition. In order to handle this drawback of the RUSLE, the SY in a certain outlet can be estimated as sediment through the use of delivery ratio [44]. It reflects substantially the ability of water flow in the watershed to transport sediment. The SDR is also to evaluate the result of soil and water conservation and treatment in a watershed. If the SDR is known, we can estimate the SY by predicting the total amount of soil loss from the RUSLE.

In fact, the sediment in watershed can originate from the slope topsoil erosion, collapse and sediment scouring and silting in the streams [16]. In Taiwan, the major sediments are fine particles, such as silt and clay that enter into Taiwanese reservoirs and watersheds, while torrents and gullies are controlled by the conservation structures or retaining works. Therefore, the slope erosion is more popular than the riverbed contribution [45]. The RUSLE model does not consider the coarse particles, so that this study attempts to integrate the RUSLE and three empirical SDR equations developed for Taiwan specifically speaking.

This study used three different empirical equations to estimate the SDR value from the relationship between SDR and catchment size and channel variables. Three empirical SDR equations developed by Chen and Lai (2006) for 10 on-stream reservoirs (As shown in Equation 11), Lai (1987) for watersheds of Zengwen Reservoir and 8 others (As shown in the Equations 12, 13) [16] were used in this study.

$$SDR_1 = 249A^{-0.316} \quad (11)$$

$$SDR_2 = 165.67A^{-0.24} \quad (12)$$

$$SDR_3 = 129.02(L/\sqrt{Sr})^{-0.19} \quad (13)$$

where A is the watershed area in km²; L is the length of mainstream in km and Sr is the slope gradient of stream bed in percentage (%).

After determining the gross erosion from the RUSLE model and SDR, sediment yield estimation for a given catchment can be defined as [46]:

$$SY_i = SDR_i * A_i \quad (14)$$

where SY_i is the sediment yield for a grid cell i ; SDR_i is the soil delivery ratio for a cell i ; and A_i is the soil loss rate predicted by the RUSLE model ($t \text{ ha}^{-1} \text{ yr}^{-1}$) for a grid cell i .

3.2.6.3 Observed sediment

The measured sediment data were obtained from the Water Resource Agency (WRA) of Taiwan over the period of 2005-2018 at 6 gauge stations located within the Zhuoshui River Basin. At each gauge station, the sediment data are sampled two to three times a month. To calculate the suspended sediment discharge (SSD), the rating curve method based on an exponential regression between the measured daily discharge Q ($\text{m}^3 \text{ s}^{-1}$) and the measured daily sediment discharge Q_s (t day^{-1}) was often utilized to estimate the annual amount of SSD. This method is widely used for SSD calculation, particularly at gauge stations where sampling frequency is unusual or insufficient [47, 48]. To reduce the residuals between the calculated and observed SSD, this study applied a modified rating curve method proposed by Kao et al. [49].

$$\beta = \frac{\sum_{i=1}^n (Q_{si} - kQ_i^b)}{\sum_{i=1}^n kQ_i^b} \quad (15)$$

where Q_{si} is the i th measured daily SSD (t day^{-1}) and Q_i is the i th measured daily water discharge ($\text{m}^3 \text{ s}^{-1}$).

From Equation (16), SSD can be estimated by the following formula:

$$\widehat{Q_{sj}} = kQ_j^b(1 + \beta) \quad (16)$$

where $\widehat{Q_{sj}}$ is the j th calculated daily SSD (t day^{-1}) and Q_j is the j th measured daily water discharge ($\text{m}^3 \text{ s}^{-1}$).

The annual SSD can be obtained from $\widehat{Q_{sj}}$ as follows:

$$\text{TSS} = \frac{365}{n} \sum_{j=1}^n (\widehat{Q_{sj}}) \quad \text{for normal year} \quad (17)$$

where TSS is the annual SSD (t yr^{-1}) and n is the number of calculated daily SSD (t day^{-1}). To make sure accuracy in statistic, the number of measured daily data should be larger than 200 days [7].

3.2.7 Result of Work Package 2

3.2.7.1 The RUSLE modeling

a. Estimating input factors of the RUSLE model

Rainfall erosivity in the Zhuoshui River Basin ranges from 4575.03 to 17544.86 $\text{MJ mm ha}^{-1} \text{h}^{-1} \text{yr}^{-1}$ with a mean value of 12351.11 $\text{MJ mm ha}^{-1} \text{h}^{-1} \text{yr}^{-1}$ and standard deviation (SD) of 2394.30 $\text{MJ mm ha}^{-1} \text{h}^{-1} \text{yr}^{-1}$. The value of this parameter tends to increase from the low plains to mountainous regions (Fig.25).

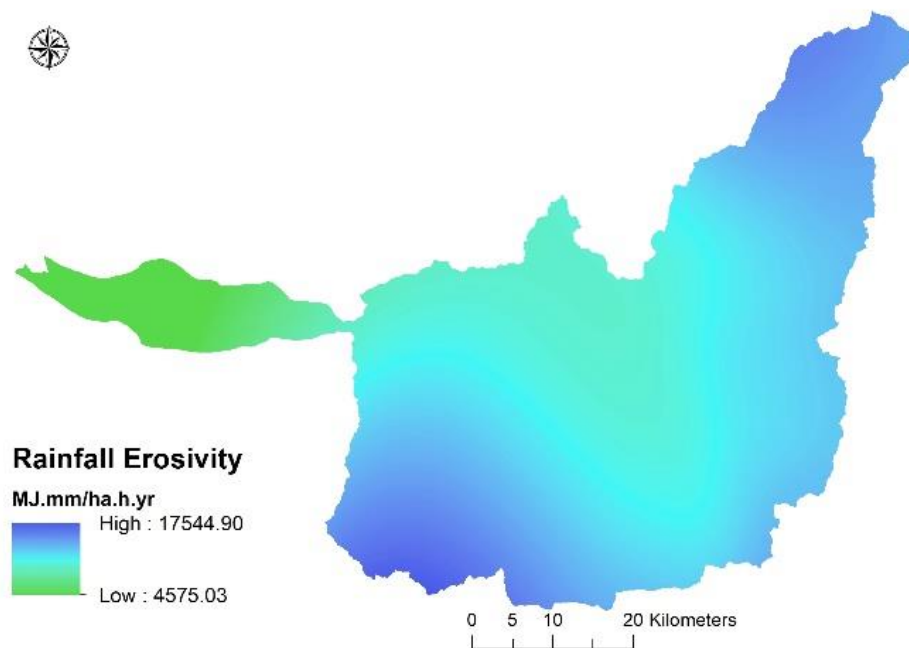


Figure 25. Rainfall erosivity.

The estimated K value varies from 0.01 to 0.065 $\text{t h MJ}^{-1} \text{mm}^{-1}$ and the mean K value is 0.04 $\text{t h MJ}^{-1} \text{mm}^{-1}$ (Fig. 26).

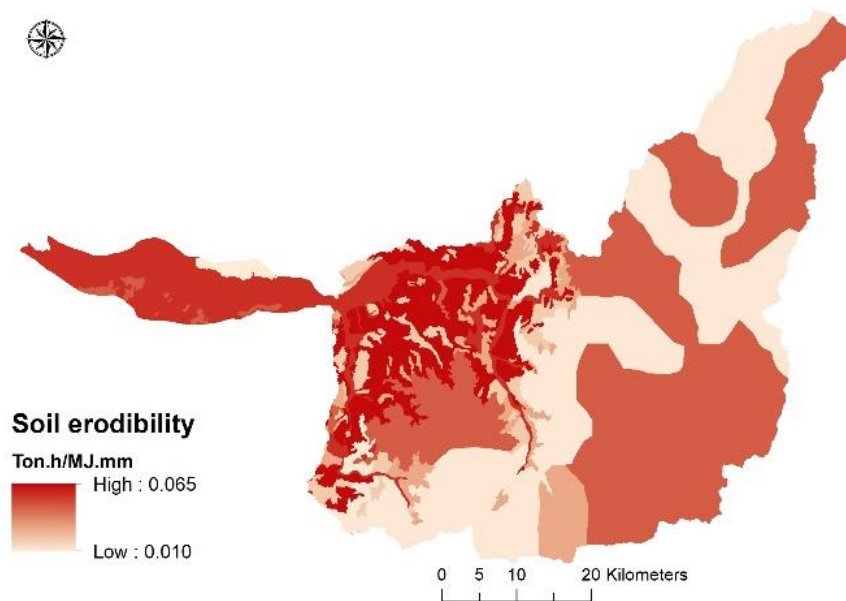


Figure 26. Soil erodibility.

The spatial distribution of the combined LS-factor is presented in Fig. 27. Due to rugged topography, the mean LS-factor's value is very high with a mean of 8.15. The highest value is found on slope land near a water body, while the bottom of the valley or low plain receives the lowest value close to zero. The increase in the LS-factor means that runoff and soil erosion will speed up at a higher rate.

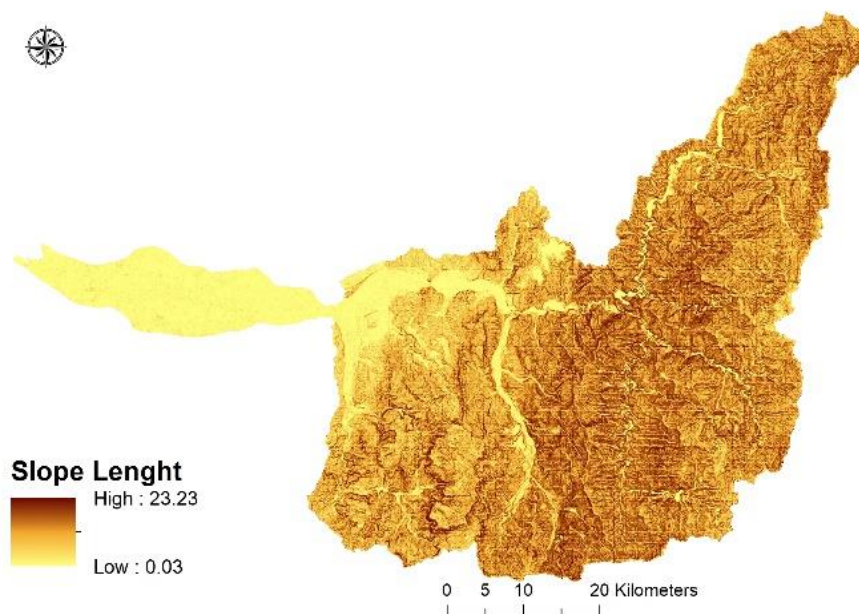


Figure 27. Slope and Length factor.

Table 10. The C value for three different years.

Year	Min	Max	Mean	Standard deviation
2005	0.00	0.99	0.07	0.10
2011	0.00	0.99	0.06	0.10
2019	0.00	1.00	0.05	0.10

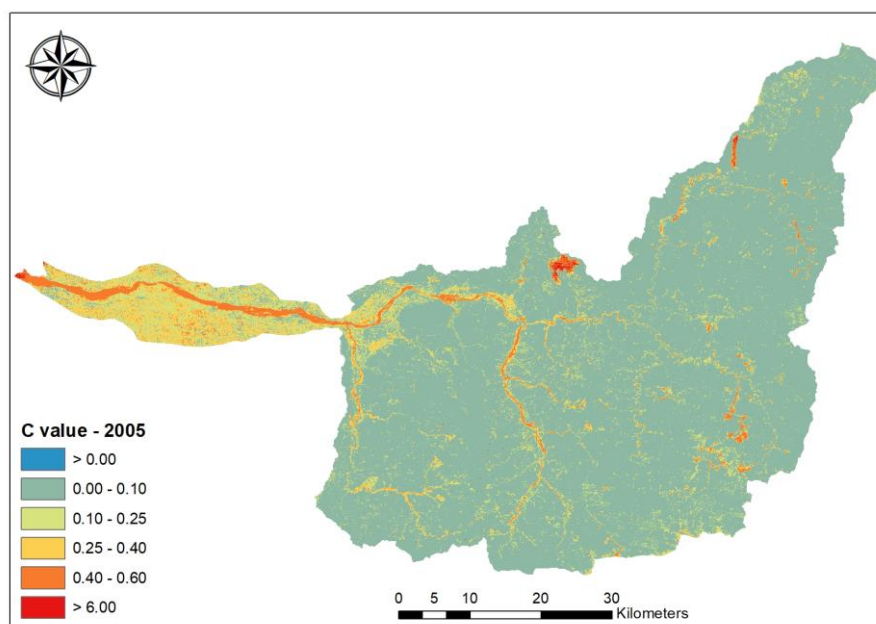


Figure 28. Average C value of 2005.

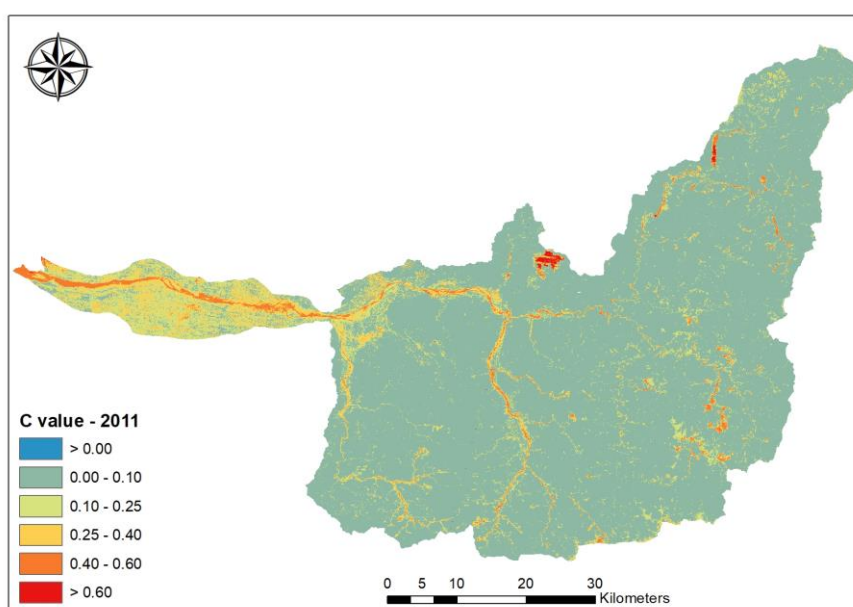


Figure 29. Average C value of 2011.

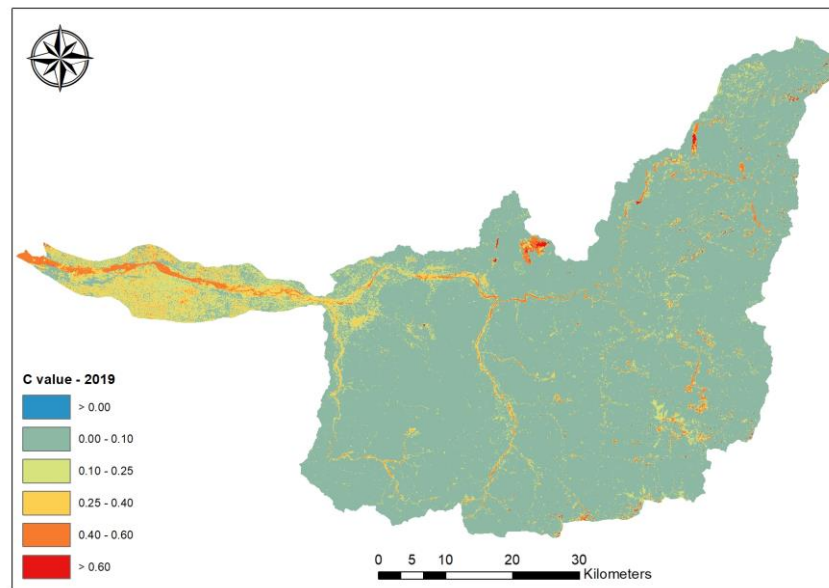


Figure 30. Average C value of 2019.

As seen in Table 10, the C value ranges from 0 to 1.0, and its mean values are 0.05, 0.06 and 0.05 in the years 2005, 2011 and 2019, respectively. The lower C value represents more effective ability of vegetation cover to protect the soil surface from erosion forcing. Generally, forest that is mainly located on the high elevation has the lowest C value close to 0. In contrast, agricultural crops that are distributed in the river valley or low plain have a higher C value. Particularly, bare land has the highest C value.

Due to the complexity and diversity in conservation practice, it is a challenging task when supporting practices will be taken into account at large scales. Although, in the ZRB, some common supporting practices have been applied to mitigate and protect the soil from erosion, such as contour farming, terrace, stone wall, etc.. These practices still differ from one farming site to another farming site as well as yearly dependent. Thus, conservation practices were estimated by using the equation from Wener (1981) to obtain the relationship between the P value and slope, which is then applied to derive the P value for the agricultural lands. Besides, the P was set to be 0 for the water and built-up land, and 1 for the other non-agricultural lands (forest and bare lands). The P values were quite similar during a given period.

Table 11. The P value for three different years.

Year	Min	Max	Mean	Standard deviation
2005	0.00	1.00	0.84	0.33
2011	0.00	1.00	0.83	0.33
2019	0.00	1.00	0.84	0.33

b. Annual soil erosion estimation

The soil erosion mapping was produced by overlaying all the five thematic layers of the RUSLE model, including rainfall erosivity factor, soil erodibility factor, slope length and steepness factor, cover, and management factor, and conservation practices factor. These factors were designed in raster format with 30×30 m resolution.

Results show that the soil loss rate during the studied period tends to gradually decrease from $133.84 \text{ t ha}^{-1} \text{ yr}^{-1}$ in 2005 to $108.47 \text{ t ha}^{-1} \text{ yr}^{-1}$ in 2019 (Table 12). After that, the soil loss rate was classified into 5 soil erosion severity classes [50, 51] (Table 13). In general, mild erosion and moderate erosion rates (from 0 to $50 \text{ t ha}^{-1} \text{ yr}^{-1}$) occur mainly in low plains, river valley, and forest-covered areas. Conversely, severe and very severe erosion rates (over $100 \text{ t ha}^{-1} \text{ yr}^{-1}$) are distributed on the sloping land with a sparse cover like bare land or upland agricultural crops.

Table 12. The soil erosion rate ($\text{t ha}^{-1} \text{ yr}^{-1}$) for three different years.

Year	Min	Max	Mean	Standard deviation
2005	0.00	10998.53	133.84	293.49
2011	0.00	7746.60	126.51	279.01
2019	0.00	11524.77	108.47	341.14
Mean of 3 years	0.00	6881.88	122.94	259.75

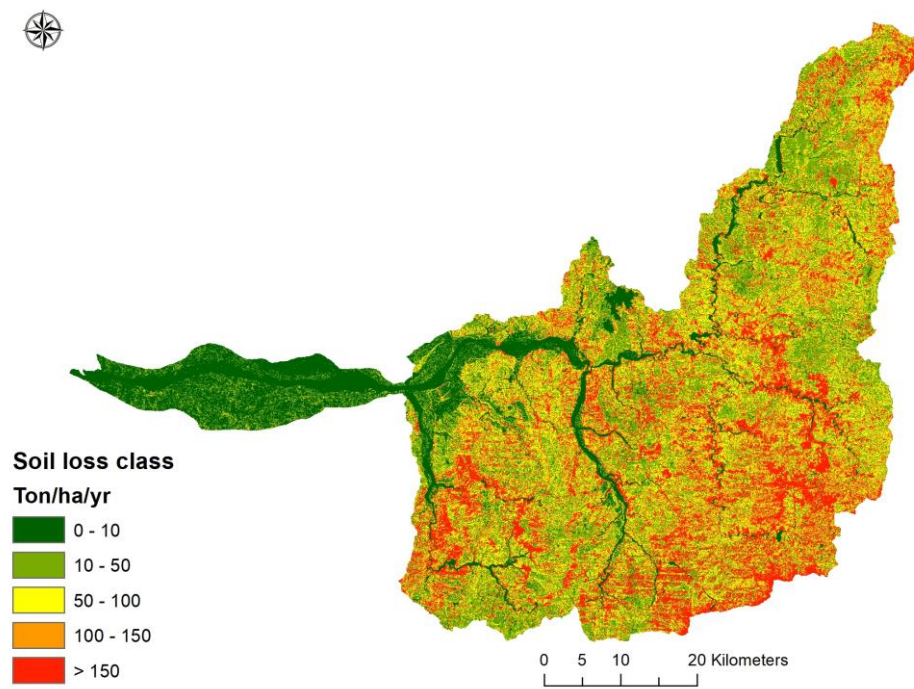


Figure 31. Soil loss rate of the year 2005.

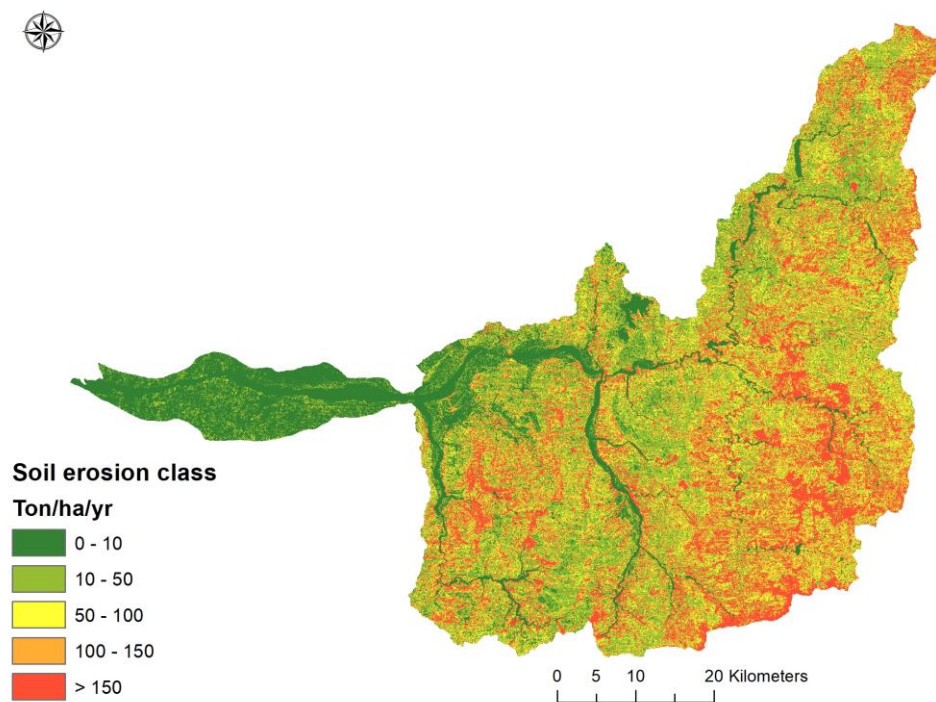


Figure 32. Soil loss rate of the year 2011.

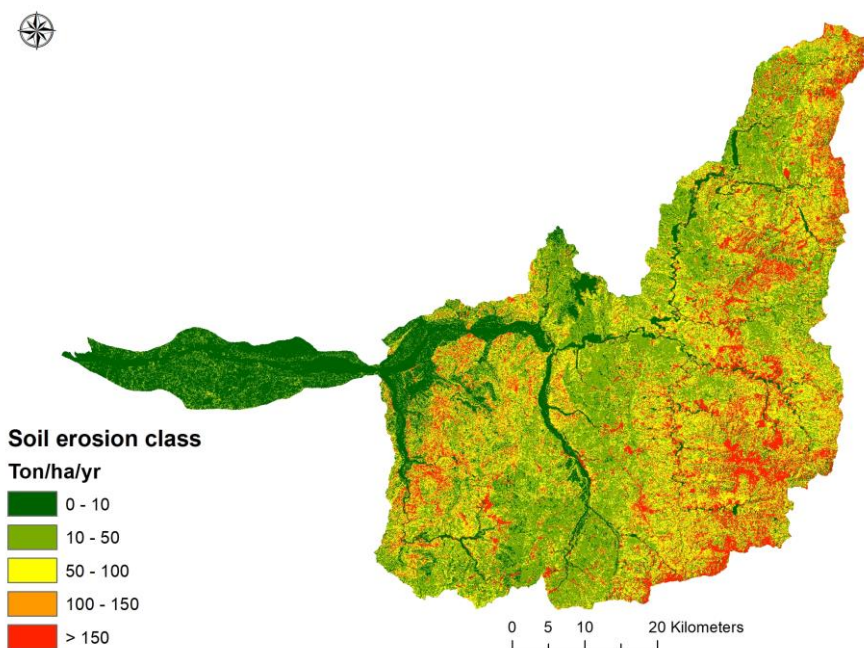


Figure 33. Soil loss rate of the year 2019.

Table 13. Classification of soil erosion rate ($\text{t ha}^{-1} \text{yr}^{-1}$).

No	Soil erosion class	Threshold ($\text{t ha}^{-1} \text{yr}^{-1}$)	2005 Per %	2011 Per %	2019 Per %
1	Mild	0 -10	17.68	15.40	18.69
2	Moderate	10 - 50	30.85	28.34	36.54
3	Moderate Severe	50 - 100	20.04	24.71	23.82
4	Severe	100 - 150	10.54	11.39	8.62
5	Very Severe	> 150	20.88	20.15	12.33

During this study period, the soil erosion rate experiences an increasing trend at mild erosion, moderate class, in which a moderate class went up by 6 % from 2005 to 2019. Conversely, severe class was decreased by 2% from 2005 to 2009, while the very severe class went down by 8% at the same time. From the results, it is clear that the soil erosion rate has been gradually reduced. In general, large areas suffered from moderate and moderate severe classes with over 50% of the total, mild erosion accounting for over 15% and the remaining percentage falling into severe and very severe classes.

c. Soil erosion rate at different land use/land cover

The LULC is considered as the most significant factor that accelerates or reduces the soil loss rate. During the study period, forest coverage remained slightly stable at around 75% of the total area. Agricultural land accounted for a minority of the study area with around 12% and this figure fluctuates at a small value. Built-up land only constituted a small percentage of the study area, so that it was increased from 1.14% in 2005 to 1.90% in 2019.

Table 14. Soil loss rate ($\text{t ha}^{-1} \text{yr}^{-1}$) at different LULC.

No	LULC	Area (ha)	Per (%)	Mean ($\text{t ha}^{-1} \text{yr}^{-1}$)	Std ($\text{t ha}^{-1} \text{yr}^{-1}$)
2005					
1	Water body	12733.65	4.02	0.00	0.00
2	Forest	239243.04	75.61	124.59	217.47
3	Bare land	20558.34	6.50	521.92	737.61
4	Built-up land	3604.41	1.14	0.00	0.00
5	Agricultural land	40284.90	12.73	32.41	96.09
2011					
1	Water body	13593.69	4.30	0.00	0.00
2	Forest	237657.96	75.11	119.81	208.70
3	Bare land	18491.49	5.84	537.10	732.10
4	Built-up land	5054.94	1.60	0.00	0.00
5	Agricultural land	41626.26	13.16	31.16	84.11
2019					
1	Water body	12455.28	4.78	0.00	0.00
2	Forest	240571.98	75.75	102.84	316.11
3	Bare land	21053.25	6.47	396.58	684.64
4	Built-up land	6175.17	1.90	0.00	0.00
5	Agricultural land	36168.66	11.11	22.79	72.05

Bare land made up 6.50% in 2005 and was reduced to 5.84% in 2011 before going up again to be 6.47% in 2019. It shared a large amount of soil erosion in total with the mean value of $396.58 \text{ t ha}^{-1} \text{yr}^{-1}$ in 2019. This figure was approximately fourth times higher than forest ($102.84 \text{ t ha}^{-1} \text{yr}^{-1}$) in 2019. As for the agricultural land, it highly suffered from soil erosion at the rate of around $22 \text{ t ha}^{-1} \text{yr}^{-1}$ in 2019. This value was slightly lower by $9 \text{ t ha}^{-1} \text{yr}^{-1}$ in 2019 than 2011 and $10 \text{ t ha}^{-1} \text{yr}^{-1}$ higher in 2019 than 2005.

3.2.7.2 Sediment delivery ratio and sediment yield prediction

To calculate the SDR from three empirical equations, firstly, the spatial boundary of each sub-basin respective to its gauge station was delineated by using DEM analysis in Hydrology and Surface tool of ArcGIS software (As presented in Figure 34). Then, the size of each sub-basin and its slope gradient and mainstream were identified. Each sub-basin represents its whole upstream area that water flows into its outlet (gauge station).

Table 15. Sediment delivery ratio for each sub-basin.

Sub-basin	Name of Gauge station	Area (km ²)	SDR ₁	SDR ₂	SDR ₃
1510H050	Yanping	85.15	61.13	57.02	89.33
1510H079	Longmen	360.37	38.75	40.33	78.62
1510H049	Neimaopu	367.17	38.52	40.15	81.42
1510H075	Bǎoshí	1576.42	24.31	28.30	63.09
1510H063	Yufeng	2096.46	22.21	26.43	61.37
1510H057	Zhang yun	2911.13	20.02	24.43	57.26

Note: Each sub-basin represents the whole upper areas that water flows into its gauge station; SDR_{1,2,3} values were obtained from SDR_{1,2,3} equations, respectively.

As seen in Table 13, SDR₁ and SDR₂ at each sub-basin range from around 20% to 61%, in which SDR₂ is slightly higher than SDR₁, except for sub-basin 1510H050.

Table 16. The predicted sediment yield (10⁶ t yr⁻¹) obtained from three SDR equations.

Sub-basin	Gross erosion (A)	SY ₁	SY ₂	SY ₃
1510H050	8.30	5.07	4.73	7.41
1510H079	46.15	17.88	18.61	36.28
1510H049	52.77	20.33	21.19	42.97
1510H075	284.05	69.05	80.39	179.22
1510H063	352.93	78.40	93.28	216.59
1510H057	429.71	86.05	104.97	246.06

Note: Gross erosion (A) is obtained from average annual soil erosion rate of the years 2005, 2011 and 2019 by using the RUSLE model; SY_{1,2,3} values are obtained from SDR_{1,2,3} equations, respectively.

As for SDR_3 , its value was from 57% to 89%, approximately 2 times more than SDR_1 and SDR_2 at the same sub-basin. Consequently, the application of the equation SRD_3 in estimating SDR for a certain sub-basin gives a higher SDR value than the equation SDR_1 and SDR_2 within the Zhuoshui River Basin.

3.2.7.3 Observed sediment calculation

In this study, annual SSD ($t\ yr^{-1}$) at 6 gauge stations was calculated by using the modified rating curve derived from the daily water discharge from 2005 to 2018 (the number of measured daily data is over 250 days). The results of the observed sediment calculation are presented in Table 17. The table shows that among gauge stations within the Zhuoshui River Basin experienced a large variation in SSD. At a dependent sub-basin, 1510H075 (Bǎoshí) that is located at the farthest distance from the downstream achieves a value of SDD at $156.50\ (10^6\ t\ yr^{-1})$, while 1510H050 (Yanping) nearby the downstream received the lowest value of $12.00\ (10^6\ t\ yr^{-1})$. The difference between two stations was around 13 times. In this period, annual SSD at downstream gauge (Zhang yun) standing for the whole upstream area was about $325.78\ (10^6\ t\ yr^{-1})$. This value means that annually the Zhuoshui River produces a massive amount of sediment from its upper streams.

Table 17. Annual suspended sediment discharge ($10^6\ t\ yr^{-1}$) at gauge stations.

Sub-basin	Name of Gauge station	Period	Number of measured days	Observed sediment
1510H050	Yanping	4/2005-2018	328	12.00
1510H079	Longmen	10/2009-2018	267	45.99
1510H049	Neimaopu	2005-2018	398	32.22
1510H075	Bǎoshí	2005-2018	443	156.50
1510H063	Yufeng	2005-2018	401	278.46
1510H057	Zhang yun	2005-2018	407	325.78

3.2.7.4 Validation of sediment yield estimation

To evaluate the model performance in SY prediction, the statistical methods including Pearson's correlation coefficient (r), coefficient of determination (R^2), and

PBIAS were calculated based on the value of the long-term simulated SY and measured SY for each sub-basin at its outlet.

$$PBIAS (\%) = \frac{\sum_{i=1}^n O_i - P_i}{\sum_{i=1}^n O_i} \times 100 \quad (18)$$

where O_i is the observed value, P_i is the predicted value and n is the number of measurements.

Table 18. Model performance statistics corresponding to
three empirical SDR equations.

Model performance	SDR ₁	SDR ₂	SDR ₃
Pearson's correlation coefficient (r)	0.96	0.97	0.97
Coefficient of determination (R ²)	0.92	0.93	0.95
PBIAS (%)			
1510H050	57.74	60.59	38.26
1510H079	61.11	59.53	21.11
1510H049	36.91	34.25	-33.35
1510H075	55.88	48.63	-14.52
1510H063	71.85	66.50	22.22
1510H057	73.59	67.78	24.47

As shown in Table 16, the estimated SY from the equation SDR_{1,2,3} reveals a strong relationship with the observed SY, in which r and R^2 values are over 9.0. However, the difference between the simulated and observed SY via PBIAS (%) is smaller by using the equation SDR₃ than the equation SDR_{1,2}. That means the SY prediction based on SDR involved catchment size gives a larger deviation than that derived from SDR related to length and slope gradient of mainstream at each sub-basin. The errors (%) in the SY estimation from SDR₁ and SDR₂ are generally over twice times as large as it from SDR₃ at each sub-basin, except for sub-basin 151H049. Applying SDR₁ and SDR₂ causes underestimation in the SY prediction for all sub-basins, and SDR₃ makes the same situation, except for sub-basin 1510H049, 1510H075 (overestimation). The predicted errors from SDR₃ at each sub-basin ranges from 14.52 to 38.26%. Compared to the previous studies [52, 53], results indicate that the combination of the RUSLE and SDR₃ produces satisfactory performance in the SY prediction at the Zhuoshui River Basin.

3.2.7.5. Discussions & Conclusion

a. Discussions:

In this study, the RUSLE model coupled with the empirical SDR equation performs satisfactorily in estimating the soil erosion and SY at the Zhuoshui River Basin. It is clear that the empirical models are developed for a certain region, thus its capacity in modelling is unexpectedly limited when applied for a new physical conditions. Due to uncertainty in identifying the RUSLE parameters and SDR, the model performance should be carefully considered and adapted to local rainfall patterns, vegetation cover and soil characteristics [9]. This study offered rainfall erosivity, soil erodibility and NDVI-based transformation for cover management, and SDRs that all were developed in environmental conditions of Taiwan may reduce uncertainty in soil erosion and SY prediction. Several authors noted that a model should be validated without any calibration steps [9, 54]. In this study, all input data for modeling were directly utilized to simulate the SY, and then the predicted SY was compared with the observed SY at gauge stations to check the ability of model operation in new situations. Currently, on-site plots for the soil loss rate measurement are unavailable or difficult to obtain to validate the RUSLE model performance at large scale [55], while the output of the RUSLE-SDR can be validated with the observed SY available at many gauge stations within watersheds. Therefore, the RUSLE-SDR approach can allow the performance of soil erosion and SY estimation to conduct rapidly and fairly at catchment scale. Although the physical-based models exhibit many advances in soil erosion modeling, empirical models often achieve more successfully and are possible to perform [56]. Managers, policy makers, and planners demand the simple predictive tools to support decision-making process rather the complicated systems [56, 57].

In fact, the RUSLE was designed to predict long-term average annual soil loss rate by inter-rill and rill erosion and it ignores gullies and stream bank erosion. Additionally, existing SY models cannot fully account for gully, bank erosion, and mass movements [58]. At a catchment scale, these soil erosion processes occur simultaneously so that it is difficult to quantify typical sediment sources separately.

Therefore, until now modeling approaches in researching soil erosion and sedimentation process still need much more efforts due to their limitations of various aspects [43]. Currently, torrents and gullies, riverbank erosion in Taiwan are mostly controlled by man-made works [45]. Hence, this study assumes that inter-rill and rill erosion are the main sources of sediment production within the study basin. Despite existing limitations, the long-term estimation of SE and SY based on the RUSLE-SDR model with the assistance of GIS and RS carried out fairly for the Zhuoshui River Basin. It is important to note that the RUSLE-SDR approach enables us to simulate soil erosion and SY in environmental conditions of the Zhuoshui River Basin, and then its capacity can be applied potentially for other catchments.

b. Conclusions:

This study applied the RUSLE-SDR model with the support of geospatial analysis and RS to estimate the long-term average annual soil erosion and SY in the Zhuoshui River Basin in Taiwan. The SDR for each sub-basin extracted from its mainstream length and slope gradient of the mainstream bed, together with the RUSLE illustrates a better prediction of soil erosion and SY than those derived from the catchment size. The annual soil erosion rate ranges from 0.00 to 6881.88 t ha⁻¹ yr⁻¹, and the average rate is 122.94 t ha⁻¹ yr⁻¹. The predicted annual SY representing for all upper streams is about 246.06 (10⁶ t yr⁻¹). This value is 24.47% lower than the observed SY at Zhang yun station. This study referred to the previous studies with involvement of empirical equations in Taiwan and then manipulated all available data for modeling to achieve satisfactory outcomes. Thus, under such circumstance, this methodology may be potentially applicable to the other catchments to help the local government consider measures for soil conservation to ensure sustainable agricultural development within a watershed.

Work package No.3:

Assessment of runoff and its relation to landslides

3.2.8 Introduction of Work Package 3

Nowadays, there are a wide range of approaches in researching landslide assessment and prediction, in which Soil Conservation Service (SCS) Runoff Curve Number (CN) model proposed by United States Department of Agriculture (USDA, 1972) is mostly used in hydrology and water resource planning of agricultural areas in the United States and other countries as well [18]. This model estimates runoff by integrating land cover types with hydrologic soil groups and data derived from the SCS table. The advantage of this model is that the user can experiment with alternate forms of land development and assess the impacts of land use scenarios might have. The model is originally developed to predict runoff volumes from agricultural fields and small watersheds. In the present, it is also applied to evaluate the landslide potentiality in the basin. USDA, 1972, for example, employed this model to determine the surface runoff from 6 sub-basins for predicting the periodical spatial distribution of slope instability and soil erosion. Landslide Potentiality Index Value (LPIV) was derived for each sub-basin to assess the sub-basin prone to landslide. In this WP, runoff estimation by using this model (SCS-CN) will be used to assess the magnitude of surface runoff and correlation analysis between the degree of surface runoff with observed landslide events to identify the threshold. It is an important information for establishing scenarios for hazard mitigation at the basin.

3.2.9 Material of Work Package 3

In order to assess the runoff for the Zhuoshui River Basin within 2005 to 2019, the SCS-CN model was applied with the support of GIS and remote sensing techniques. The input data below were collected from various sources;

- Digital Elevation Model (DEM) with the 30-m resolution was download from the USGS website;
- Long-term annual rainfall was collected from 49 meteorological stations within and surrounding the Zhuoshui River Basin;

- Soil information from the Soil map of Taiwan;
- Landslide occurrence of the years from 2005 to 2017 were obtained from Soil and Water Conservation Bureau Council of Agriculture, Executive Yuan.

3.2.10 Methodology of Work Package 3

3.2.10.1. Modeling the runoff

The SCS-CN model was originally developed by the U.S. Department agriculture for agricultural watersheds in the mid-western U.S. However, it has been used throughout the world far beyond its original developers. This method takes into account the land use/land cover, hydrological soil cover, and antecedent moisture conditions for predicting the runoff from the basin.

The basic equation of this method is mentioned as below [59]:

$$\frac{(P-I_a)-Q}{S} = \frac{Q}{(P-I_a)} \quad (19)$$

or

$$Q = \frac{(P-I_a)^2}{(P-I_a)+S} \quad (20)$$

where,

P = precipitation in millimeters ($P \geq Q$);

Q = runoff depth (mm);

S = potential maximum retention (mm); and

I_a = initial abstraction.

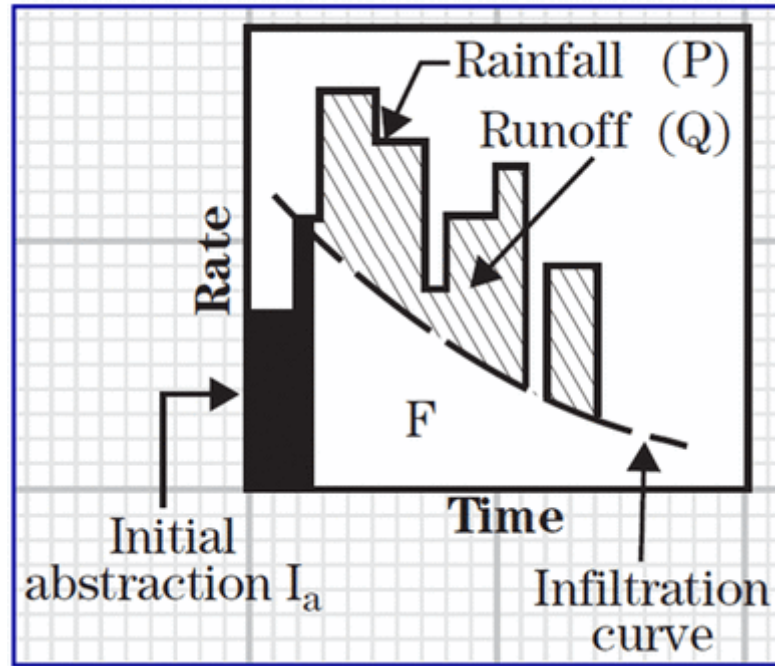


Figure 34. Components of SCS runoff equation [59].

a. Precipitation (P)

P is the maximum precipitation in a given period. In the study, the annual rainfall (mm) was used for calculating the runoff depth. The long-term rainfall data from 49 meteorological stations were obtained with their geographical locations. Similar to the WP2, the annual rainfall distribution for the whole basin was interpolated based on the station position and elevation by using the Co-Kriging method.

b. Potential maximum retention (S)

S is the potential maximum soil moisture retention after runoff begins. S is calculated via the below formula:

$$S = 25.4 * \left(\frac{1000}{CN} - 10 \right) \quad (21)$$

where CN is hydrologic soil-cover coefficient

Curve number (CN) is usually determined from the look-up table based on the soil type and land use.

Table 19. Hydrologic soil group (HSG) for the USDA soil texture classes [59].

HSG	Soil texture class
A	Sand, loamny sand, or sandy loam
B	Silt or loam
C	Sandy clay loam
B	Clay loam, silt clay loam, sandy clay, silty clay, or clay

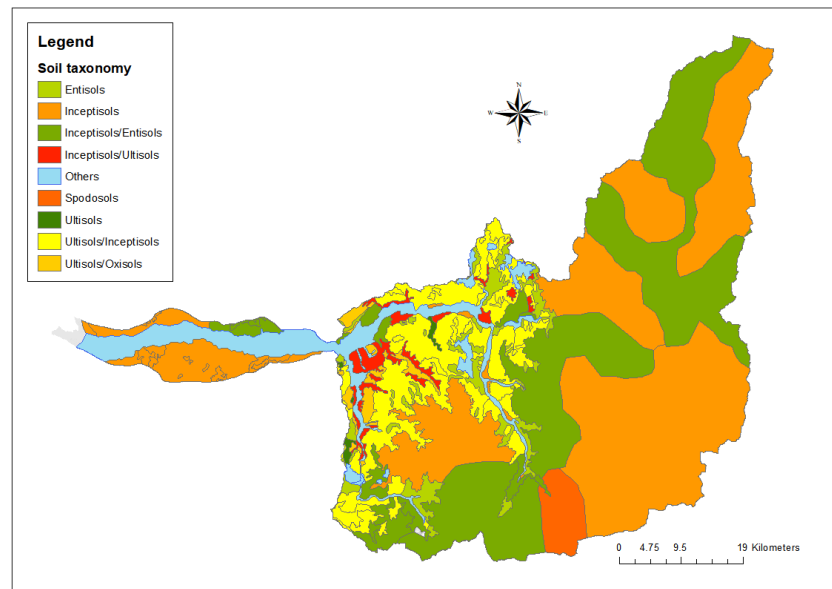


Figure 35. The soil taxonomy of the Zhuoshui River Basin.

Actually, the soil system database of Taiwan does not consist of soil textures. Hence, we based on the soil taxonomy (Figure 35), soil type (Figure 23 of WP2) of the Zhuoshui River Basin, and profile characteristics of each soil taxonomy in the Soils of Taiwan book [60] to estimate the component of each soil classification. For example, with Entisols taxonomy, based on Table 5.6, page 59 of the book, we estimate the type of soil has loam, Clay loam, Sandy loam or Silt loam. After that, each type was assigned to the groups A, B, C or D of HSG based on the Table 19. Finally, from the land use/land cover classification results for the year of 2005, 2011, and 2019, the CN value was obtained based on the below table.

Table 20. CN value base on HSG and land cover [73].

No	LULC	CN A	CN B	CN C	CN D
1	Water body	100	100	100	100
2	Forest	30	55	70	77
3	Bare land	68	79	86	89
4	Built - up land	57	72	81	84
5	Agricultural land	64	75	82	85

c. Initial abstraction (I_a)

Initial abstraction I_a is the total amount of water losses before forming runoff. There are some losses of water, such as surface depression, evaporation, infiltration and so on. I_a varied highly, but generally has correlation with soil and land cover parameters:

$$I_a = 0.2 * S \quad (22)$$

3.2.10.2. Assessment the relation between Runoff and landslide

In order to assess the relation between runoff and landslide, the frequency ratio was applied through three steps. Firstly, the annual runoff was classified into 7 classes, under 1500 mm; 1500 – 2000 mm; 2000 – 2500 mm; 2500 – 3000 mm; 3000 – 3500 mm; 3500 – 4000 mm; and more than 4000 mm. Secondly, the yearly landslide inventory in polygon was converted into points by the ArcGIS software. The last step used the frequency ratio method to assess the relation between runoff and landslide.

Table 21. Runoff classification into 7 classes.

No	Thresholds (mm)
1	<1500
2	1500 -2000
3	2000 - 2500
4	2500 - 3000
5	3000 - 3500
6	3500 - 4000
7	> 4000

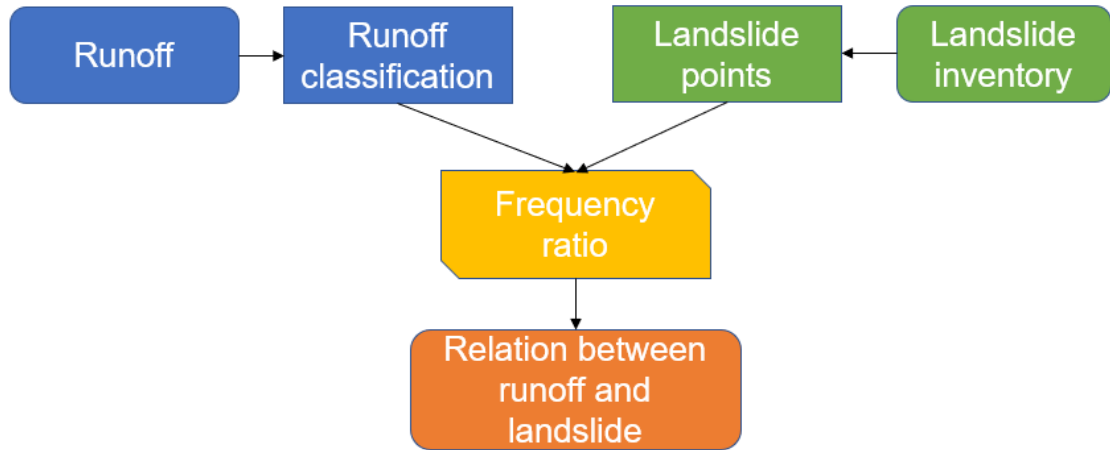


Figure 36. Flow chart to assess the relation between runoff and landslide.

The frequency ratio formular is below [61]:

$$FR = \frac{E/F}{M/L} \quad (23)$$

where,

FR: Frequency ratio for runoff with landslide occurrence;

E: Number of landslide pixels for each class of runoff;

F: Total number of landslide pixels in study area;

M: Number of pixels of each class of runoff; and

L: Total number of pixels in study area

3.2.11 Result of Work Package 3

3.2.11.1. The SCS-CN modeling

a. The CN value

The CN values were calculated for the three years 2005, 2011, and 2019. The results show that the hydrologic soil-cover coefficient (CN) ranges from 55 to 100 for the three years. The highest value of CN is observed at the water area like rivers, lakes (Sun Moon Lake), and reservoirs. Conversely, the lowest value is located in the forest.

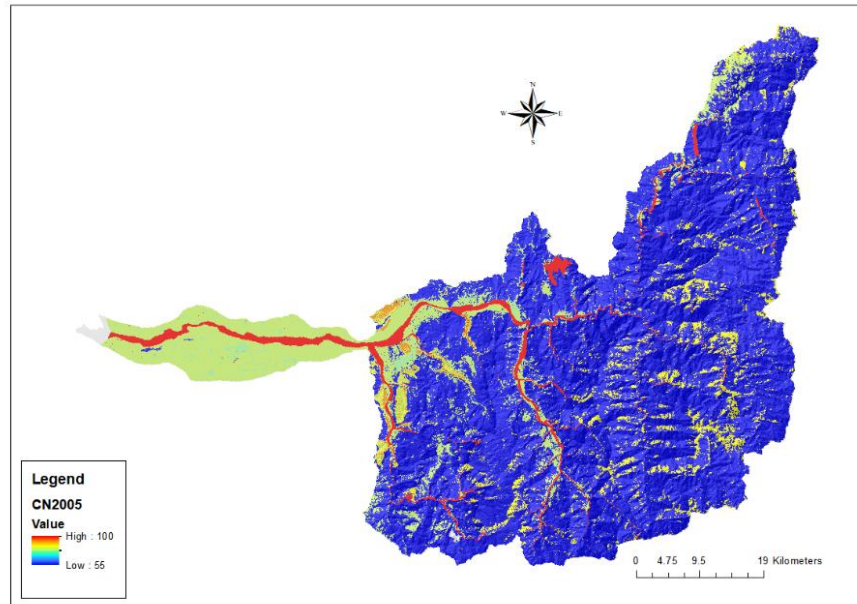


Figure 37. The CN value of 2005.

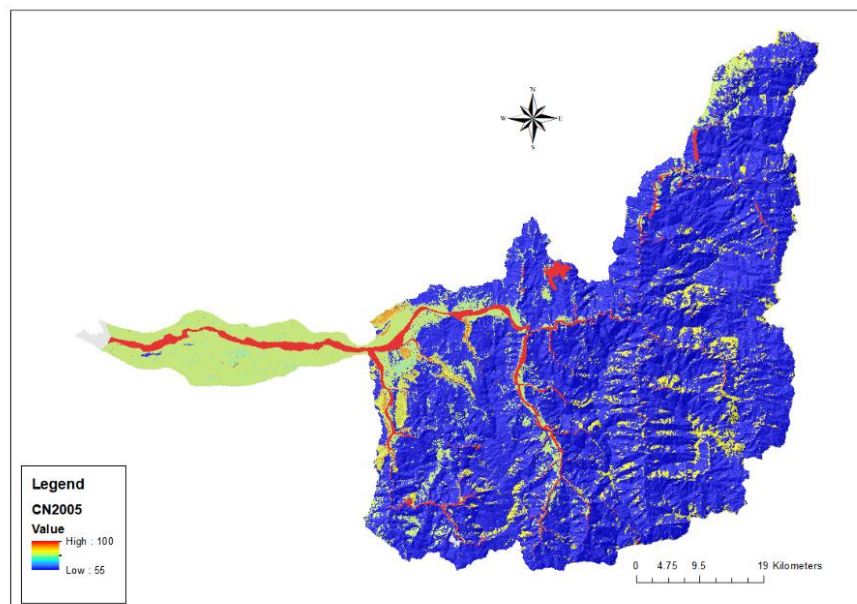


Figure 38. The CN value of 2011.

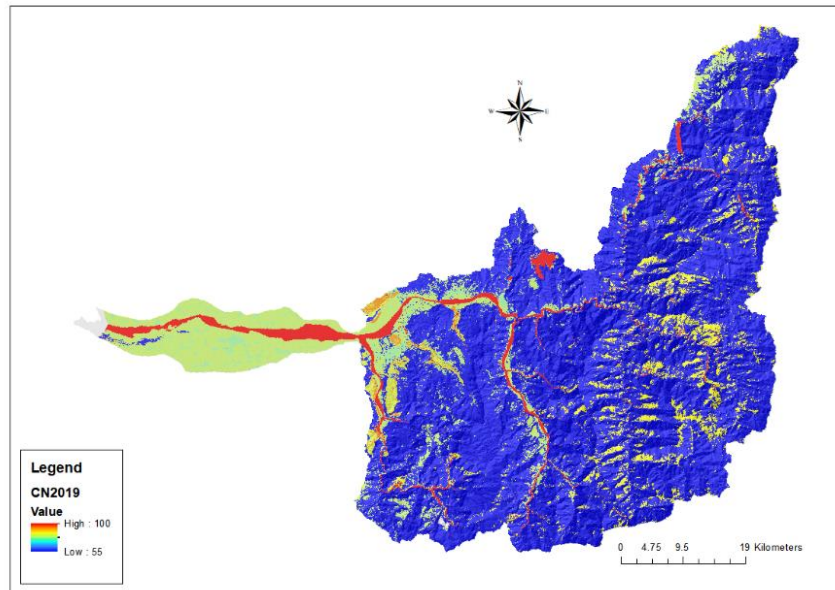


Figure 39. The CN value of 2019.

Table 22. The CN values for three difference years.

Year	Min	Max	Mean	Standard deviation
2005	55	100	61.24	11.69
2011	55	100	61.36	11.83
2019	55	100	61.12	11.60
Mean of 3 years	55	100	61.24	11.71

During the study, the dynamic of LULC obtained from Landsat image classification shows that the LULC has not significantly changed in the Zhuoshui River Basin. Therefore, the CN values for three difference years 2005, 2011, and 2019 changed slightly. The CN values fluctuate around 61.24 with values of 61.24, 61.36, and 61.12 for 2005, 2011, and 2019, respectively.

b. Potential maximum retention (S)

The potential maximum retention S was generated based on the equation 22. From the results, all three years have the same range of value for S, from 0 to 207.82 with mean value of 165.06. At the south and east of the Zhuoshui River Basin, where have the forest, the potential retention of water is the highest. While at the west side, the S value is lower due to the development of built-up here.

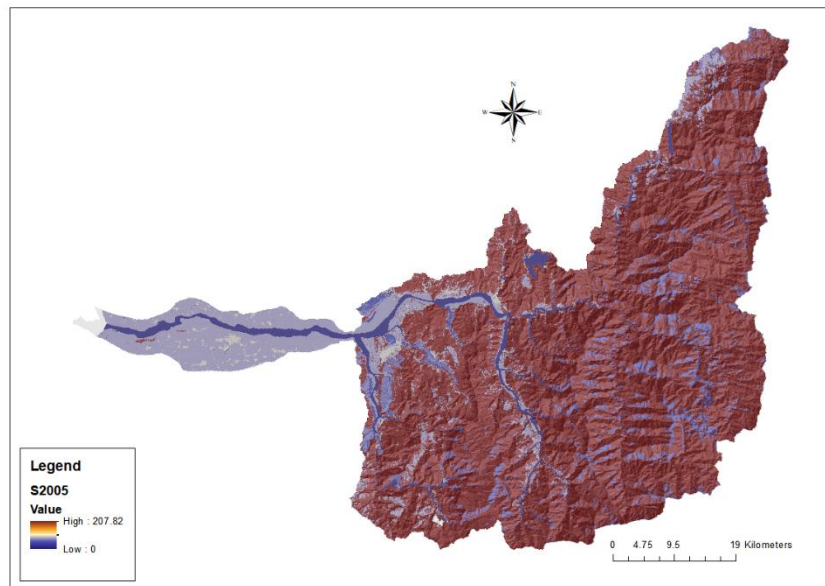


Figure 40. The S value of 2005.

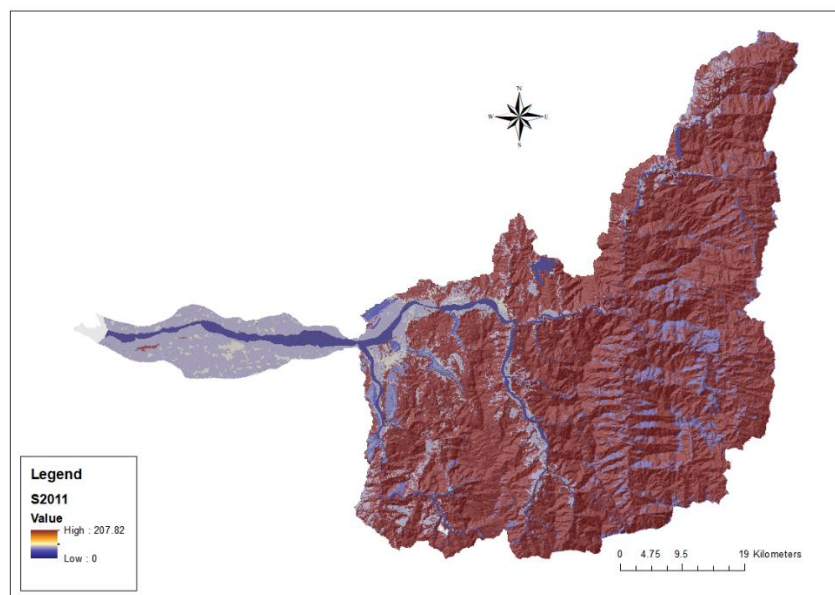


Figure 41. The S value of 2011.

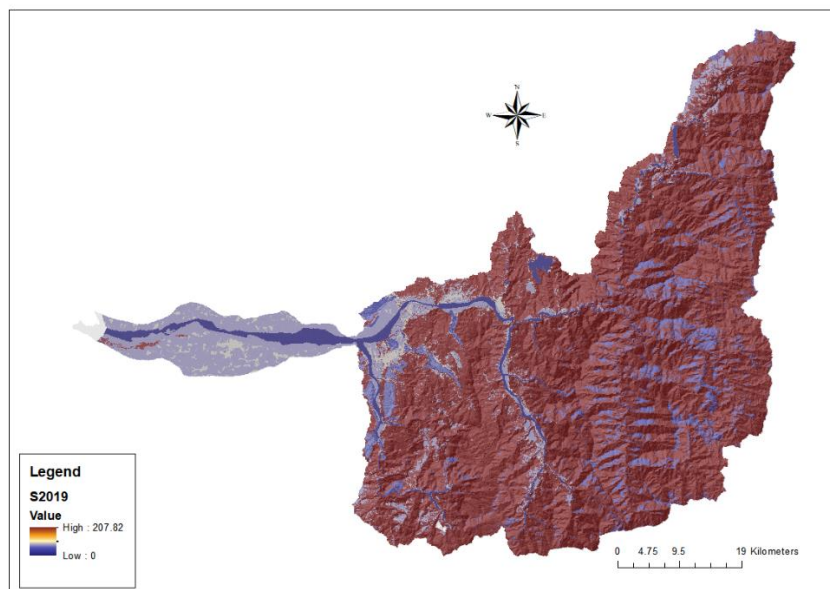


Figure 42. The S value of 2019.

Table 23. The S values for three difference years.

Year	Min	Max	Mean	Standard deviation
2005	0	207.82	172.63	62.86
2011	0	207.82	171.97	63.38
2019	0	207.82	173.28	62.41
Mean of 3 years	0	207.82	172.63	62.88

c. Runoff

Runoff is the output of SCS-CN model. In this study, the annual runoff for 15 years from 2005 to 2019 were calculated. Runoff of each year depends on the accumulated rainfall of that year. For LULC, it is not changed much though. Thus, this study assumes that the runoff in 2005 to 2008 were calculated based on LULC in 2005; the runoff in 2009 to 2014 were calculated based on LULC in 2011; and the runoff in 2015 to 2019 were calculated based on LULC in 2019.

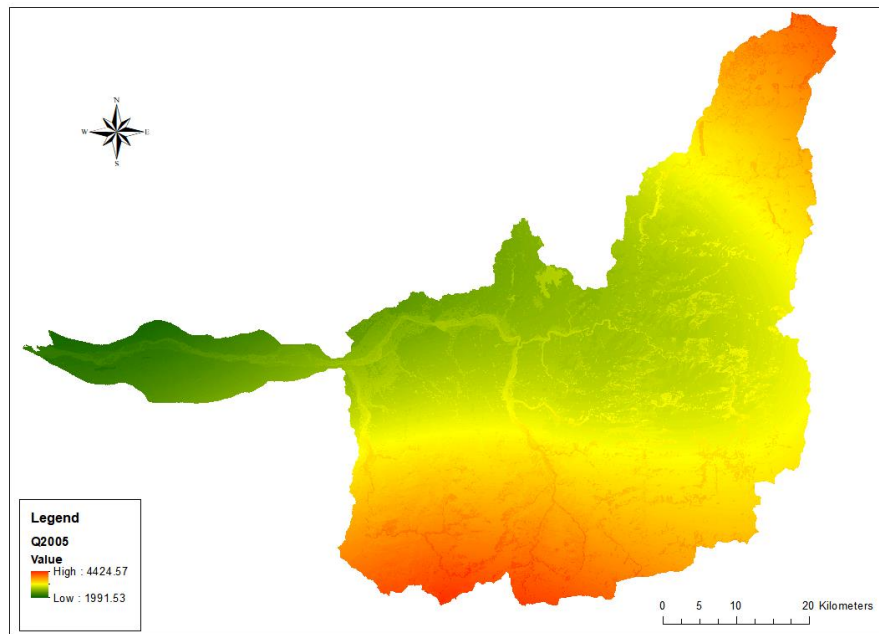


Figure 43. The runoff distribution in 2005.

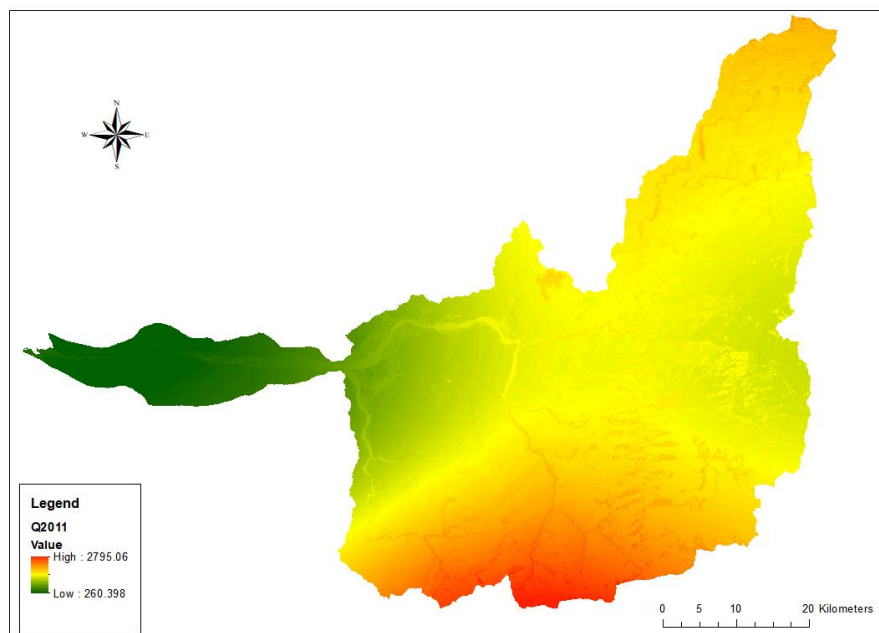


Figure 44. The runoff distribution in 2011.

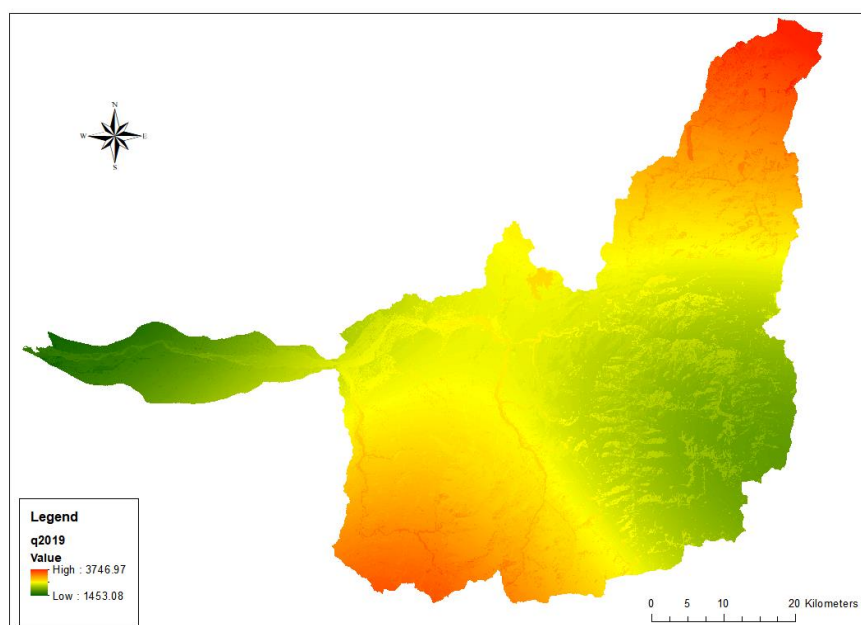


Figure 45. The runoff distribution in 2019.

Table 24. The accumulated annual runoff values (mm) from 2005 to 2019.

Year	Min	Max	Mean	Standard deviation
2005	1991.53	4424.57	3160.51	473.12
2006	1493.65	4273.86	2989.28	469.95
2007	2040.24	3404.32	2883.66	202.98
2008	1545.93	4235.13	3208.40	430.13
2009	1106.64	3725.11	2126.63	502.41
2010	1130.75	2904.51	1918.36	275.37
2011	260.40	2795.06	1489.10	433.40
2012	1654.68	4257.41	2924.68	417.23
2013	1934.84	3402.41	2687.32	214.78
2014	904.43	2654.03	1834.61	284.61
2015	1005.00	2337.79	1445.43	289.11
2016	1273.88	3824.39	2467.59	398.36
2017	1267.70	3641.26	2497.35	453.63
2018	1147.65	2776.59	1777.94	315.43
2019	1453.08	3746.97	2517.48	401.63
Mean	1347.36	3493.56	2395.22	370.81

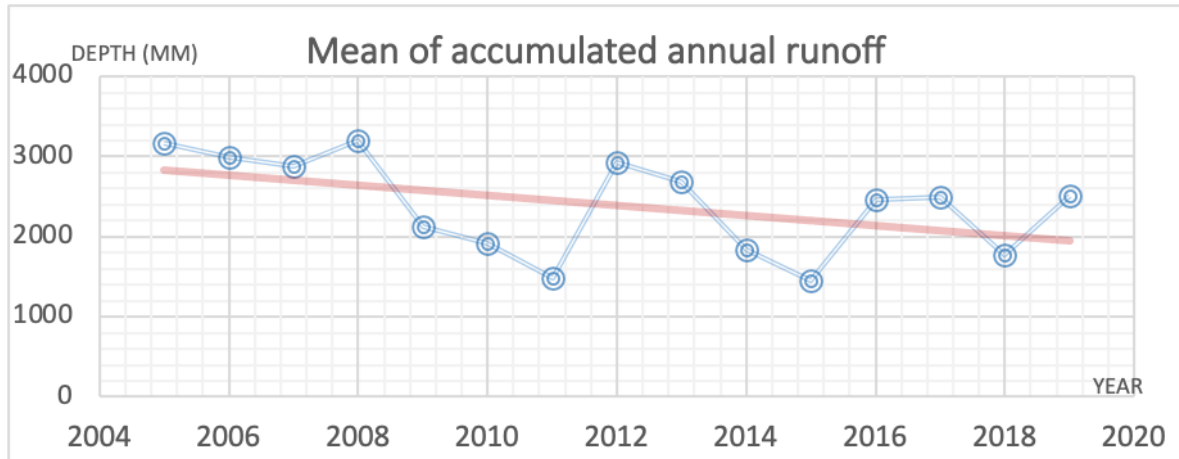


Figure 46. Mean of accumulated annual runoff of the Zhuoshui River Basin.

As seen in Table 24, the minimum value of annual runoff at the Zhuoshui River Basin is 1347.36 mm with maximum value up to 3493.56 mm, and mean value 2395.22 mm. The mean accumulated annual runoff in 2005 and 2008 were the highest in 15 years. Both of them are larger than 3000 mm, while in 2011 and 2015, these values are only around 1500 mm. For the whole period, we can see that, there is a slide decrease in runoff from 2005 to 2019.

3.2.11.2. Validation of the runoff

To evaluate the SCS-CN model performance in runoff prediction. We used the total runoff volume of each sub-basin and compared with the total flow measured in the respective year. The statistical methods, including Pearson's correlation coefficient (r), coefficient of determination (R^2), and PBIAS (As presented in the equation 18) were calculated based on the value of annual runoff simulated by the SCS-CN model and measured total volume in a year for each sub-basin at its outlet.

$$W_i = Q_i * A_i \quad (24)$$

where W_i is the total volume of year i ; Q_i is runoff prediction by SCS-CN model in year i , and A_i is the area of sub-basin i .

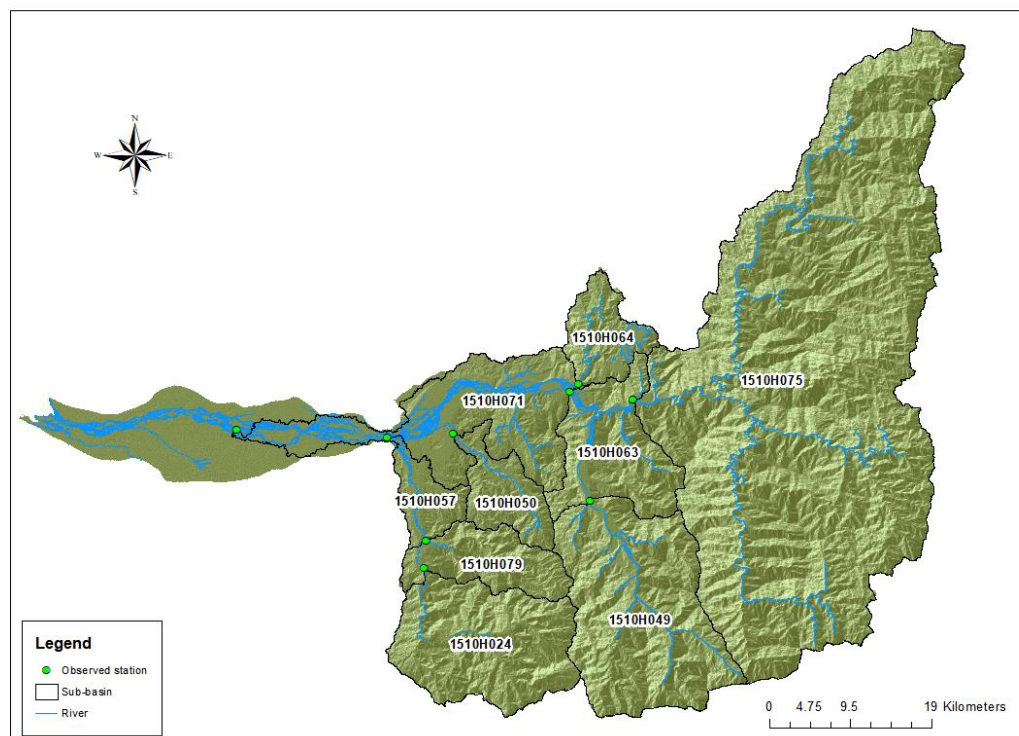


Figure 47. Sub-basins of the Zhuoshui River Basin.

Table 25. Model performance statistics.

Code station	Station	R	R ²	PBIAS (%)
1510H075	Bǎoshí	0.88	0.77	5.04
1510H071	Xi zhou da	0.85	0.71	-1.31
1510H063	Yufeng	0.80	0.64	10.99
1510H050	Yanping	0.59	0.34	12.37
1510H057	Zhang yun	0.77	0.59	10.07
1510H049	Neimaopu	0.48	0.23	19.92

The model performance shows that, there are good relationships between the runoff predicted by the SCS-CN model and the observed data, in which the Pearson's correlation coefficient (R) of Zhang Yun, Yufeng, Xi zhou da and Bǎoshí are over 0.77. The R values of Nemaopu and Yanping are still low though with values only 0.48 and 0.59, respectively. PBIAS shows the difference of the predicted and observed data. All of 6 stations have difference lower than 20%. The station Xizhouda (1510H071) is nearly the total outlet of whole basin with the best performance between the predicted and observed value (R = 0.85; PBIAS = -1.31%), while the

Neimaopu station (1510H049) has the worst results ($R = 0.48$; $PBIAS = 19.92\%$). In reality, the flows at stations of rivers are usually impacted by many factors, such as the operation of reservoirs upstream, the intake water for domestic demand or other irrigation, and industry demand. In the Zhuoshui River Basin, there are some reservoirs or hydropower plants like MingTan, Dagan, Wushe, Wujie reservoirs. They operate the flow for downstream, leading to additional errors in validating the simulated value and observed value.

3.2.11.3. Assessment of the relation between runoff and landslide

Landslide inventories were collected from the Soil and Water Conservation Bureau Council of Agriculture, Executive Yuan for the years from 2005 to 2017.

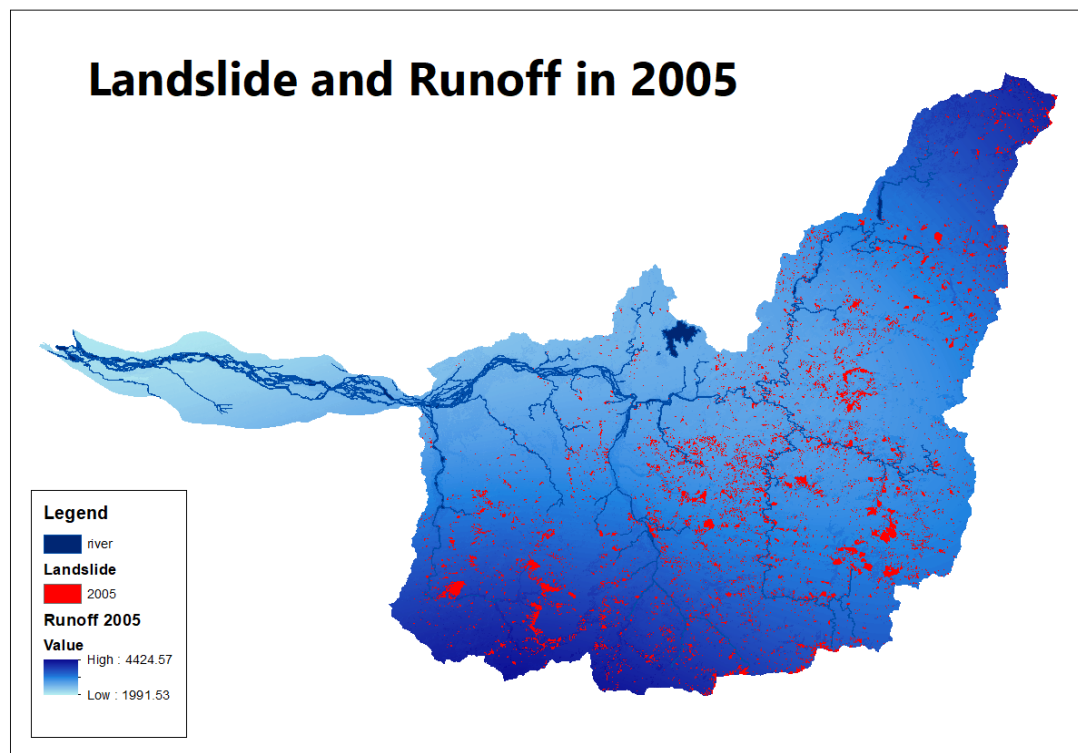


Figure 48. Landslide and runoff in 2005.

Based on the frequency ratio method and landslide (LS) inventory data from 2005 to 2017, we calculated the ratio of number of LS pixels for each class of runoff and total number of LS pixels in whole study area and also the ratio of number pixels of each class and total number pixels in the study area.

Table 26. The frequency ratio of LS on each class of runoff.

Classes	2005	2006	2007	2008	2009	2010	2012	2013	2014	2015	2016	2017	Average
<1500					0	0	0		0.09	11.8	0	0	2.0
2000	0	0		0	9.32	10.9	10.9	0	10.3	7.5	0	9.81	6.2
2500	0.03	0	0	0	11.4	10.4	10.9	6.87	14.4	15.3	9.46	13.4	8.9
3000	7.04	3.71	3.36	3.18	8.85	23.4	9.96	10.2	54.7		13.7	7.56	15.3
3500	14.1	6.32	11.8	12.3	20.3		10.7	18.6			14.4	12.5	15.5
4000	12.6	8.59		12.8	50.2		15.1				21.3	61.6	30.0
>4000	13.9	14.3		26			22.7						22.2

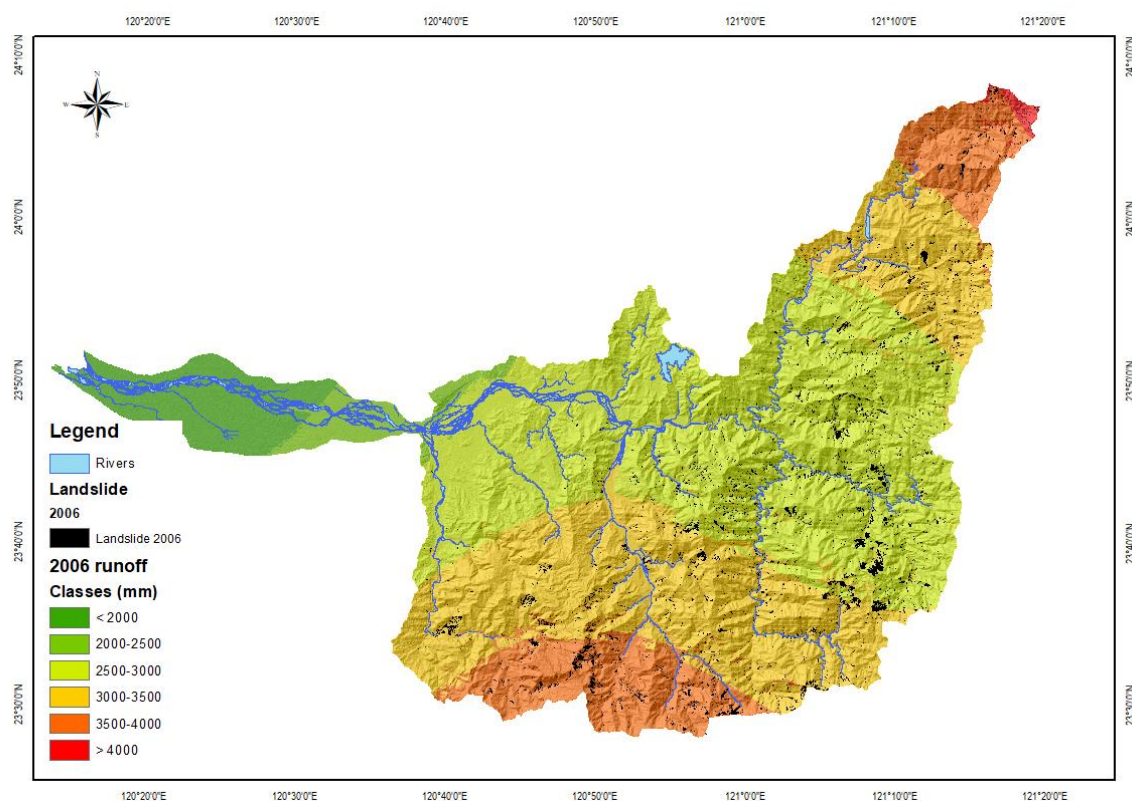


Figure 49. Runoff classification and LS occurrences in 2006.

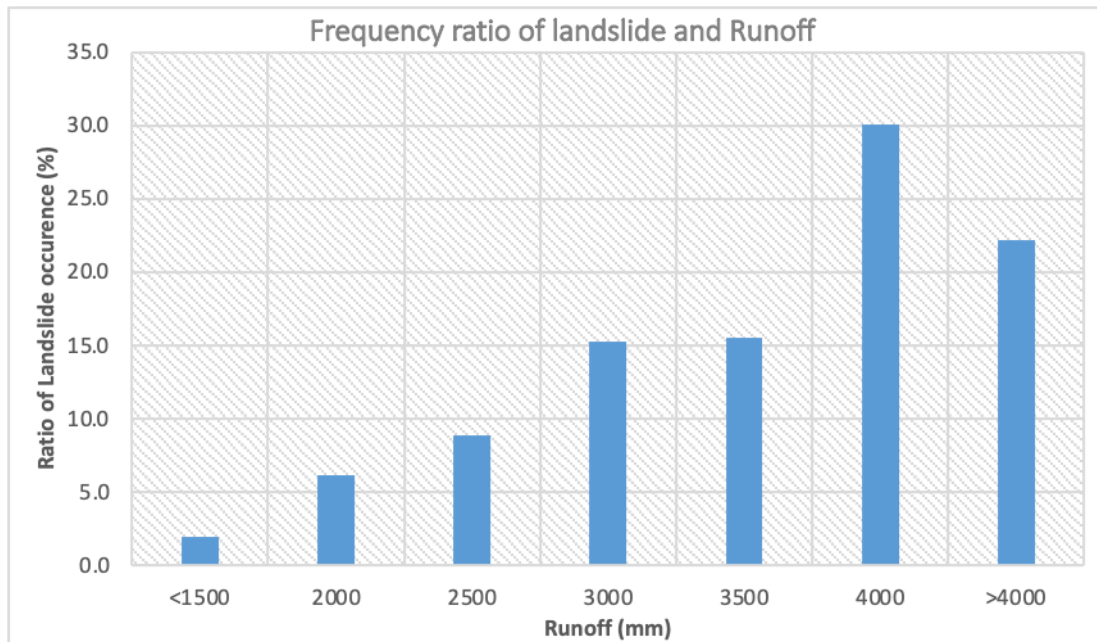


Figure 50. The long-term frequency ratio of LS occurrences on runoff.

The result of estimation the frequency ratio of LS occurrence on runoff shows that, there are low ratio of LS occurrence on lower 2500 mm of runoff. They account for 8.9%, 6.2%, and 2.0% for runoff of 2500 mm, 2000 mm, and lower than 1500 mm classes respectively. Besides that, the LS appeared significantly when runoff increases from 2500 mm to 3000 mm and 3000 mm to 3500 mm. They account for 15% ratio. For area with runoff more than 3500 mm, the ratio of LS occurrence increases even up to 30% (4000 mm) and 22% (>4000 mm).

3.2.12 Conclusion of Work Package 3

In this study, we applied the SCS-CN model to estimate the annual runoff for the Zhuoshui River Basin from 2005 to 2019. We also used the frequency ratio method to analyze the relationship between runoff and landslide occurrence. The results of the annual runoff were validated by comparing with the observed flow data at 6 measurement stations. The mean accumulated annual runoff at the Zhuoshui River Basin shows that there is a slight decrease in the runoff for the whole basin in the last 15 years. Runoff on the surface is one of the important factors that lead to landslide happening. The results of this study showed that landslide is highly likely to occur at areas that have runoff above 3000 mm yr⁻¹.

Work package No.4:

Establishment of land use scenarios based on land capability to mitigate soil erosion within the Zhuoshui Rive Basin

3.2.13 Introduction of Work Package 4

Soil conservation has been an emerging issue, which receives much attention worldwide since 1980 due to its negative impacts on both on-site and off-site land cover. Thus, the programme or action regarding soil erosion control at various scale has been launched to maintain and improve the soil productivity as well as environmental quality. Soil conservation aims to reduce soil erosion to a rate at which agricultural and non-agricultural activities can be profitably obtained from a conserved area without unexpected environment threats [56]. The principles of soil conservation is the intervention on erosion forcing regarding the detachment and transport process by raindrop, surface runoff [56]. According to Sheng [62], watershed planning needs to concern land use and land capability; conservation farm planning; and planning for sustainability. To optimize the land use properly in a watershed, it is necessary to set certain criteria or limits in various purposes. Such criteria need to be followed by the planners to classify whole land into capacity or suitability classes. Land capability is extracted from the physical properties and can be assumed as a constant for that land unit. Ideally, whole land within a watershed can match against its capability. In fact, many areas are placed in unreasonable purposes that cause a wide range of negative impacts [63]. Planners can identify the site whether or not is it misused by comparing its location with the current land use before proposing the plans for proper management [62]. This theory should be followed by the implementing organizations in all activities involved in the land conservation [63].

Due to physically unfavourable conditions, about 1.3 million ha of hilly area in Taiwan is prone to water erosion, in which 0.6 million ha are eroded and 0.3 million ha are severely eroded [19]. Therefore, the allowable land use classification for the slope land has received much attention in Taiwan since 1953. In 1976, the Taiwanese government proposed a standard guideline for the slopeland capability classification (SLCC) [19]. This framework classifies the land capacity into I-VI classes based on

slope gradient, soil effective depth, soil erosion degree and parental rock properties [64]. The outcome of SLCC can help the local farmers select a suitable land use for cultivation. Besides, it also provides valuable information for the soil and water conservation [19]. This guideline of SLCC is only applied for the field survey in land capability classification, so it needs to be adapted to conduct at large scale. Soil erosion magnitude, for example, is difficult to quantify at regional scale with field investigation. However, soil and water conservation needs knowledge on the spatial pattern of soil erosion. Thus, soil erosion modeling at catchment scale is a promising tool for soil and water conservation purposes [57]. The physically-based model has advantages in research purposes, but it requires huge input data leading to uncertainty in soil erosion prediction. Simple or empirical models are widely used due to their low input data requirement and comprehensive structure [57]. In this study, soil erosion assessment by using the RUSLE model can identify areas prone to soil erosion at different spatio-temporal coverages. SLCC intensively needs field inventory to collect data on slope gradient, soil depth, parent material, particularly soil erosion symptoms and rate of soil loss, which impractically conduct at wider areas under the constraint of field investigation (the rugged terrain condition and inaccessibility). Thus, we adapt SLCC to determine the utilization of slope land for the Zhuoshui River Basin by using spatial analysis. Some alternative methods in SLCC in Taiwan were also done by the previous studies. Chang [65] used DEM, topographic wetness index (TWI) and USLE (Universal Soil Loss Equation) to delineate SLCC at Chen-You-Lan Watershed with GIS analysis. Compared to the SWCB field survey, the outcome of this study gives an overall consistency of 78%. Lo [66] combined the modified “simple-accurate” method and the AGNPS (Agricultural Non-Point Source) model to assess the land use suitability at Shuilin Stream watershed (Nantou County).

3.2.14 Mapping slopeland capability classes of Work Package 4

This study adapted the standard guideline for SLCC to establish the land capacity classes at the Zhuoshui River Basin with the support of GIS technique. SLCC can be mapped at each pixel at 30 m resolution based on slope gradient, soil depth and soil severe degree (As presented in Table 27).

Table 27. Data used for mapping the slopeland capability classification.

Data	Sources
Slope gradient	Interpolated from SRTM downloaded from USGS
Soil depth	Collected from SWCB
Soil severe degree	Extracted from the result of the RUSLE modeling in 2019

Slope gradient in percentage was derived from STRM and then classified into 6 classes [66]. Soil depth information was obtained from SWCB including 4 soil-depth classes, while soil erosion was assumed severe as a soil loss rate over 100 t ha⁻¹ yr⁻¹ from annual soil erosion modeling by the RUSLE in 2019.

Table 28. Input parameters for slopeland capability classification.

Slope gradient (%)						
Class	1	2	3	4	5	6
Slope	<5	5-15	15-30	30-40	40-50	>55
Per%	5.78	10.53	11.72	10.39	17.81	43.77
Soil depth (cm)						
Class	Very deep		Deep	Shallow	Very shallow	
Depth	>90		50-90	20-50	<20	
Per%	1.82		3.12	94.56	0.97	
Soil erosion estimation (t ha ⁻¹ yr ⁻¹) by using the RUSLE model						
Class	Mild	Moderate	Moderate severe		Severe	Very severe
SE rate	0-10	10-50	50-100		100-150	>150
Per%	18.69	36.54	23.82		8.62	12.33

Note: Slope gradient and soil depth classes were referred from SWCB

As seen in Table 28, slope steepness over 55% is dominated with 43.77%, which covers the whole area at the eastern and southern sites, while slope gradient under 15%

is distributed at the low plain and stream valley that only accounts for a small proportion of the total area at around 16%. The other slope gradient classes have a scattered distribution in all most mountain areas.

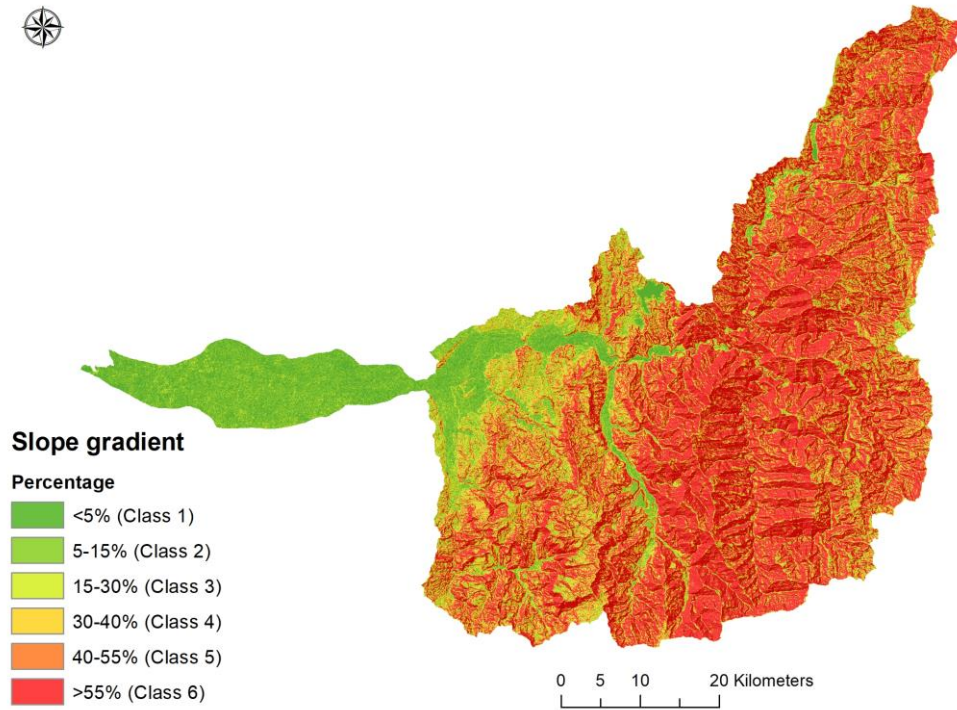


Figure 51. Slope gradient classes.

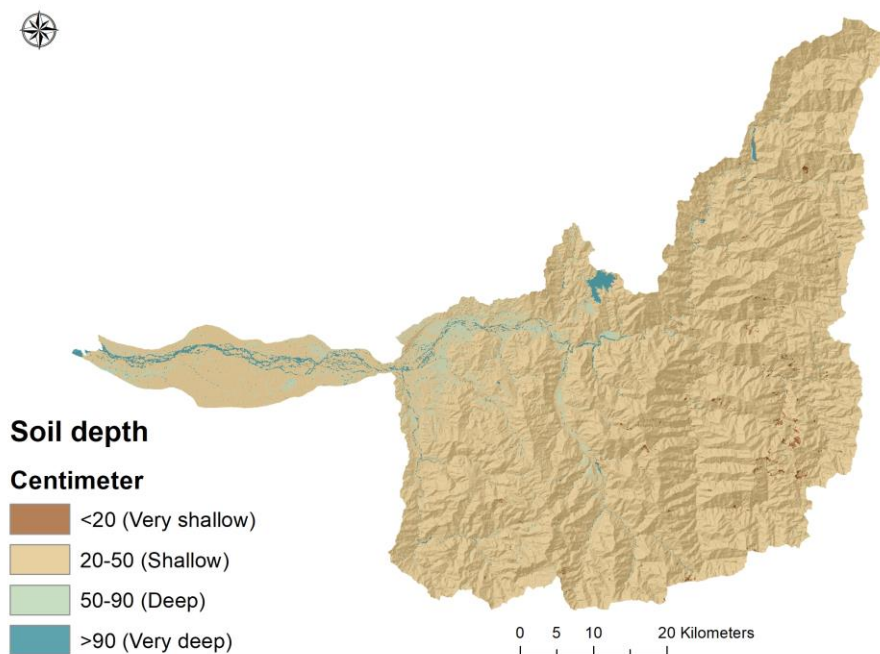


Figure 52. Soil depth classes.

Soil depth is an important factor that has a strong effect on the soil productivity. However, 94.56% of the total area is shallow with soil depth of 20-50 cm that might cause the limitation in the agricultural activities. A minor proportion of area has soil depth over 50 cm (4.94%) and 0.95% of the total area is very shallow (under 20 cm).

According to the RUSLE model, severe soil erosion was assumed at the rate over 100 t ha⁻¹ yr⁻¹ for the SLCC analysis, which occupies nearly 21% of the total area.

After preparing all input parameters for SLCC, we adapted the matrix of SLCC from SWCB to identify the five suitable classes for various purposes (As seen in Figure 53). The spatial distribution of each class is presented in Figure 54 and its purposes and soil erosion control requirements are described in Table 29.

Soil depth	Slope gradient (%)					
	<5%	5-15%	15-30%	30-40%	40-55%	>55%
Very depth >90 cm	Class I Crop and Pasture land	Class II Crop and Pasture land		Class III Crop and Pasture land	Class IV-1 Crop and Pasture land	Class V Forest land
Depth 50-90 cm			Class III Crop and Pasture land			
Shallow 20-50 cm	Class II Crop and Pasture land	Class III Crop and Pasture land			Class IV-2	
Very shallow <20 cm				Class IV-2		
						Severe soil erosion

Figure 53. Slopeland capability classification adapted from SWCB

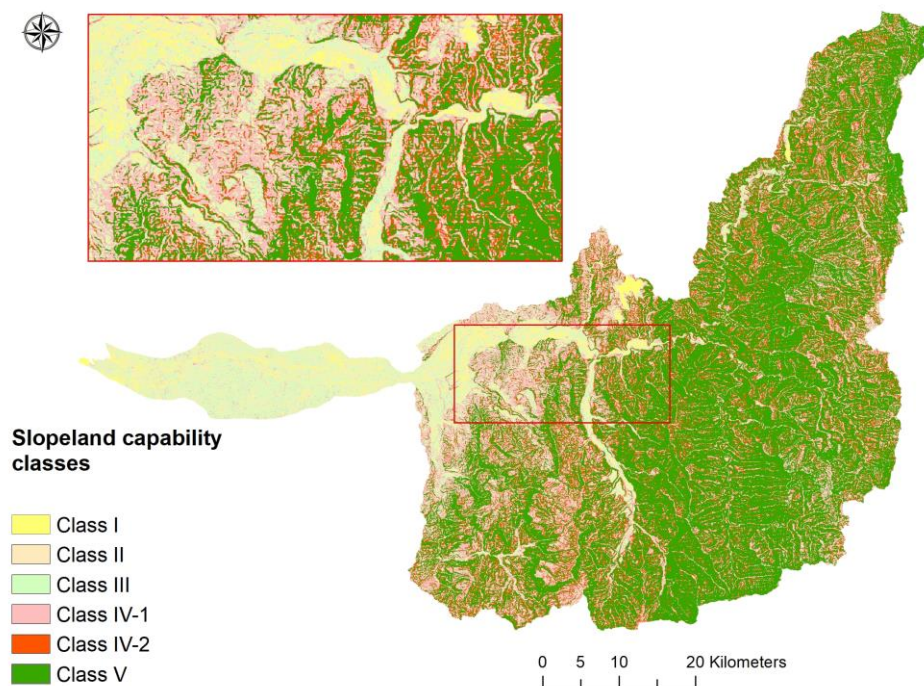


Figure 54. Spatial distribution of SLCC in this study area.

Table 29. Land capability class and its treatments.

Land capability class	Purposes	Treatments	Area (ha)	Per %
Class I	Land suitable for agricultural and pasture	Unrestricted agricultural use	5625.27	1.78
Class II	Land suitable for agricultural and pasture	Need moderate soil and water treatments	19816.11	6.26
Class III	Land suitable for agricultural and pasture	Need intensive soil and water treatments	28458.63	8.99
Class IV-1	Land suitable for agricultural and pasture	Suited for perennial fruit trees and pasture which provide year round vegetative cover with minimum tillage.	68095.80	21.52
Class IV-2	Land suitable for agricultural and pasture	Erosion control measures should be dictated by local authority, if crops requiring frequent tillage are to be planted.	41208.66	13.02

Class V	Land suitable for forestry	Natural forest should be maintained, or restoration be enforced. Severe erosion may take place at the early state of reforestation. Necessary erosion control measures should be taken. Special conservation measures should be prescribed by local authority	153219.60	48.42
Total			316424.00	100.00

From Table 29, land suitable for forest accounts for a large proportion area with 48.42%, while land preferred to agricultural purposes without any restricted measurements is only under 2%. The rest area needs to be moderate and intensive treatments for soil erosion control if it is used for the agricultural activities (49.80%). Results of SLCC indicate that land resource is limited to the use for agricultural and pasture purposes and it requires strict measures in controlling soil erosion on steep slopes. Nearly a half of the whole basin is preferred to forestry or conservation purposes.

3.2.15 Establishing land use scenarios to reduce soil erosion of Work Package 4

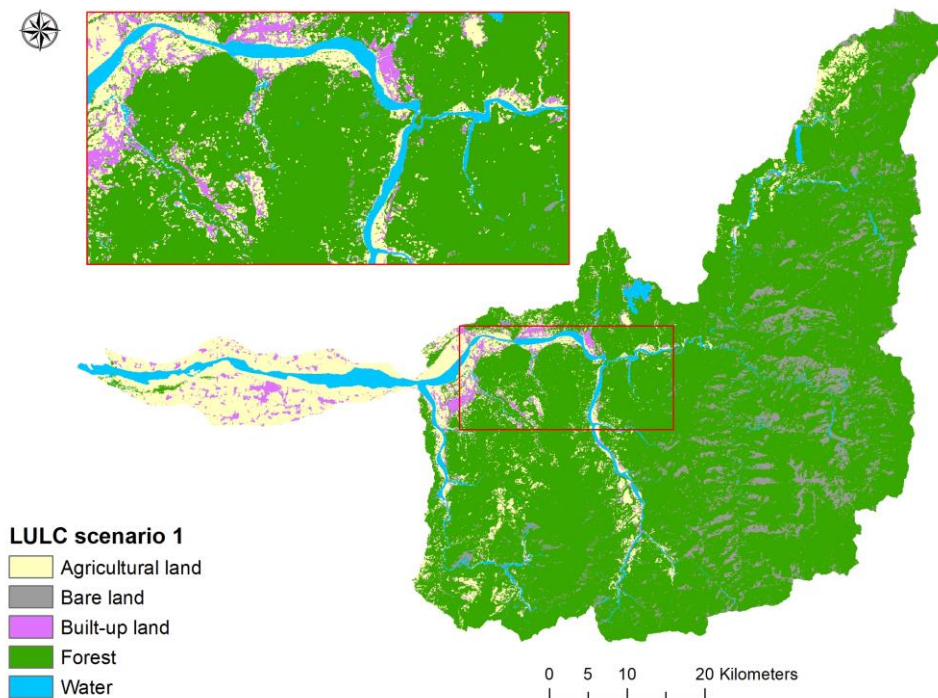
Soil erosion is a common form of land degradation process over the world so that it causes severe constraints in sustainable agriculture and environmental issues. Vegetation covers, land use types and land use intensity are crucial contributing factors on the magnitude and frequency of overland flow and soil erosion [67]. Therefore, land use change will result in adverse consequences on sedimentation, water quality, soil productivity decline in many mountainous regions. Thus, land use planning for the watershed will identify what particular uses are most suitable under each major land use, in which land capability assessment is an important process in determining the different uses suitable to a given area [68]. As for the soil erosion mitigation in this study, we attempt to develop land use scenarios based on land capability to reduce soil erosion rate at the Zhuoshui River Basin.

3.2.15.1 Scenario 1: Current LULC and conservation practices.

Table 30. Percentage of each LULC according to to SLCC.

LULC	Slope Land Capability Classification					
	Class I	Class II	Class III	Class IV-1	Class IV-2	Class V
Water	0.53	1.23	1.27	0.54	0.10	0.17
Forest	0.16	0.83	2.63	17.82	12.18	42.42
Bare land	0.00	0.04	0.16	0.99	0.43	5.02
Built-up land	0.11	0.57	0.90	0.32	0.03	0.01
Agricultural land	0.97	3.50	4.03	1.85	0.28	0.80

This LULC scenario proposes the conservation treatments by using the present LULC (2019) based on the Slope Land Capability Classification. In this case, except for the other LULC types, agricultural land requires conservation treatments according to its SLCC. Agricultural land located at Class I, for instance, does not require any modified conservation treatments. However, moderate to intensive conservation treatments must be applied for the agricultural land belonging to Class II-IV.

**Figure 55.** LULC scenario 1.

From Table 30, agricultural land makes up only 0.97% under Class I without any restricts of conservation, 7.53% under Class II and III that requires moderate and intensive conservation. The remainder (0.28%) is under Class IV preferred to perennial trees with intensive conservation practice. The misuse of agricultural land is 0.80%. In fact it is suitable for forestry purposes.

In general, the current LULC in the Zhuoshui River Basin is distributed appropriately, only small proportion of built-up land (0.01%) and agricultural land (0.8%) must be adjusted due to their overlap with Class V (forestry). In addition, bare land might be mainly caused by landslide in steep areas accounting for 6.65% of the total area, and bare land located at Class V occupies 75.45% of the total bare land area. Hence it is in need of converting to forest for the eco-environmental protection.

3.2.15.2. Scenario 2: LULC transformation based on SLCC

This scenario recommends that all LULC types will be allocated to suit with their SLCC, except for water and built-up land. These kinds of LULC are impractical to covert to other LULCs. This plan can optimize the use of land resource, particularly agricultural land that matches with its allowable capacity.

Table 31. Scenario 2 for LULC transformation in accordance with SLCC.

LULC	Slopeland Capability Classification					
	Class I	Class II	Class III	Class IV-1	Class IV-2	Class V
Water	0.53	1.23	1.27	0.54	0.10	0.17
Forest	<u>0.16</u>	<u>0.83</u>	<u>2.63</u>	<u>17.82</u>	<u>12.18</u>	42.42
Bare land	<u>0.00</u>	<u>0.04</u>	<u>0.16</u>	<u>0.99</u>	<u>0.43</u>	<u>5.02*</u>
Built-up land	0.11	0.57	0.90	0.32	0.03	0.01
Agricultural land	0.97	3.50	4.03	1.85	0.28	<u>0.80*</u>

Note: Number is the area converted to agricultural land

Number* is the area converted to forest

According to this scenario, forest that occupies 33.61% of the total area will be shifted to agricultural land, in which Class IV-1 and Class IV-2 cover 29.52% of the total area. Only 3.62% converted from forest to agricultural land belongs to Class I-III.

Therefore, the potential land for agricultural expansion is very limited for crop production, while large area (30.00%) for perennial trees can be cultivated at Class IV-1 and Class IV-2 with intensive conservation practices. Additionally, bare land is also a potential source in providing space for agricultural activities, but it is mostly acceptable to perennial plantation (1.42% of total), only 0.20% of total area for agricultural land at Class II and III. Moreover, forest can be increased by 5.02% from bare land and by 0.80% from agricultural land if the two kinds of land belonging to Class V will be transformed. In brief, this scenario has an advantage in enlarging the agricultural land from forest and bare land. Yet it will significantly make forest reduction leading to eco-environmental problems.

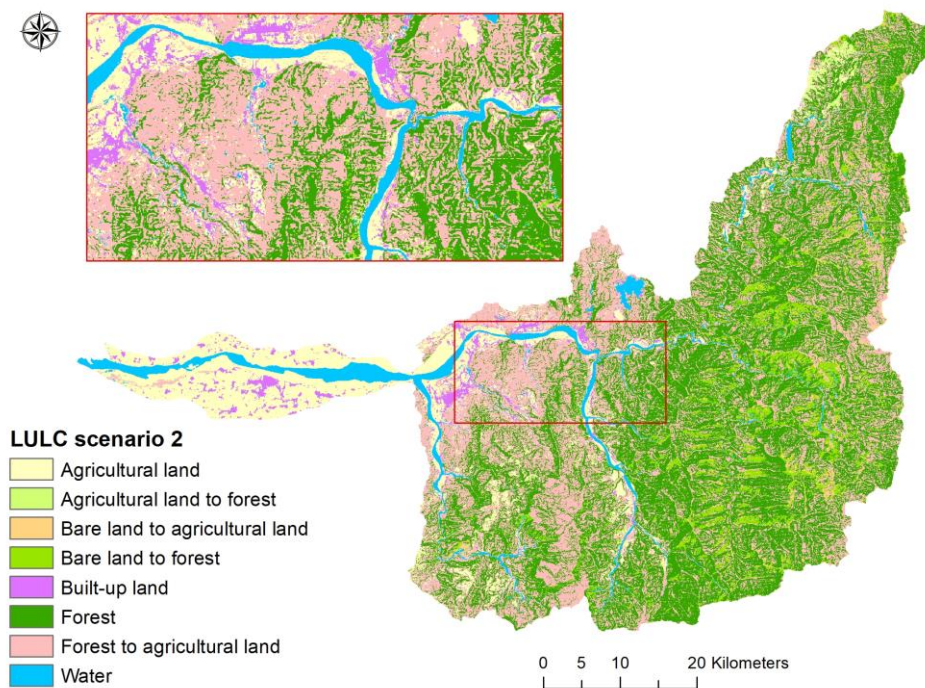


Figure 56. LULC scenario 2.

3.2.15.3 Scenario 3: Trade-off between agricultural development and eco-environmental protection

This scenario aims to achieve a balance between agricultural expansion and environmental protection. For this purpose, forest (3.62%) and bare land (0.20%) distributed on Class I, Class II and Class III will be converted to agricultural land (3.82%), while bare land (6.44%) and agricultural land (2.93%) belonging to Class

IV-1 and Class IV-2 and Class V will be changed into forest (9.37%). As a result, forest area will be expanded by 5.75% and agricultural land will be increased by 0.89% after LULC transformation.

Table 32. Scenario 3 for LULC transformation in accordance with SLCC.

LULC	Slopeland Capability Classification					
	Class I	Class II	Class III	Class IV-1	Class IV-2	Class V
Water	0.53	1.32	1.27	0.54	0.10	0.17
Forest	<u>0.16</u>	<u>0.83</u>	<u>2.63</u>	17.82	12.18	42.42
Bare land	0.00	<u>0.04</u>	<u>0.16</u>	<u>0.99</u> *	<u>0.43</u> *	<u>5.02</u> *
Built-up land	0.11	0.57	0.90	0.32	0.03	0.01
Agricultural land	0.97	3.50	4.03	<u>1.85</u> *	<u>0.28</u> *	<u>0.80</u> *

Note: Number is the area converted to agricultural land

Number is the area converted to forest*

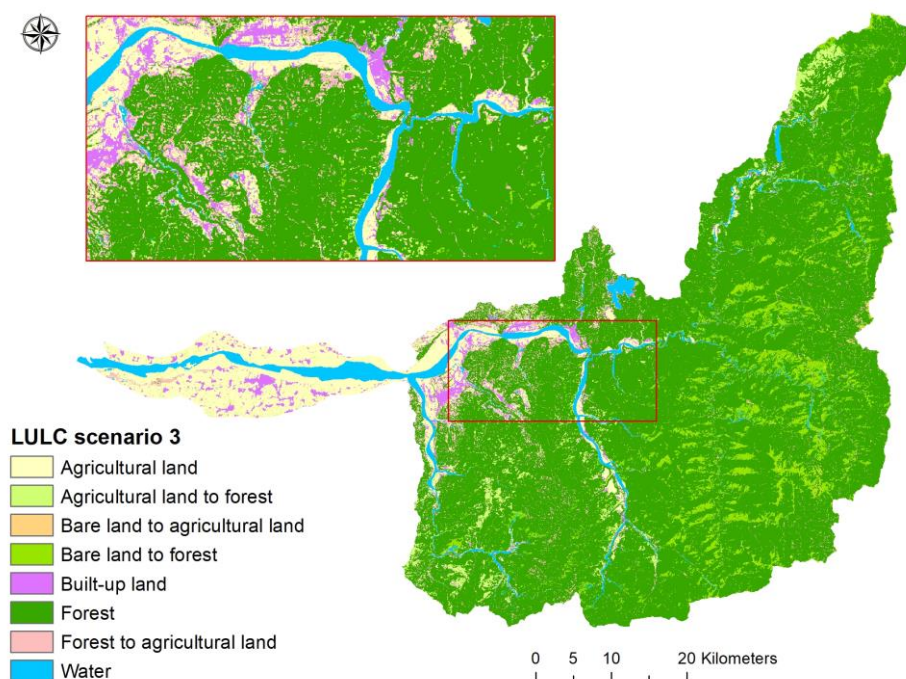


Figure 57. LULC scenario 3.

3.2.15.4 Scenario 4: Eco-environmental priority

In this plan, the whole bare land converted to forest (6.65% of total) and

agricultural land that are located at Class IV-1, Class IV-2 and Class V will be shifted to forest (2.93% of total).

Table 33. Scenario 4 for LULC transformation in accordance with SLCC.

LULC	Slopeland Capability Classification					
	Class I	Class II	Class III	Class IV-1	Class IV-2	Class V
Water	0.53	1.32	1.27	0.54	0.10	0.17
Forest	0.16	0.83	2.63	17.82	12.18	42.42
Bare land	<u>0.00</u>	<u>0.04</u>	<u>0.16</u>	<u>0.99</u>	<u>0.43</u>	<u>5.02</u>
Built-up land	0.11	0.57	0.90	0.32	0.03	0.01
Agricultural land	0.97	3.50	4.03	<u>1.85</u>	<u>0.28</u>	<u>0.80</u>

Note: Number is the area converted to forest

From this scenario, forest restoration activities will be prioritized to help forest area increase by 9.58% in the study area. That means the total of forest area will achieve the highest coverage at 85.61% within the Zhuoshui River Basin. Conversely, agricultural land after transformation will be reduced by 2.93% and only maintain at 8.50% of total belonging to Class I-III.

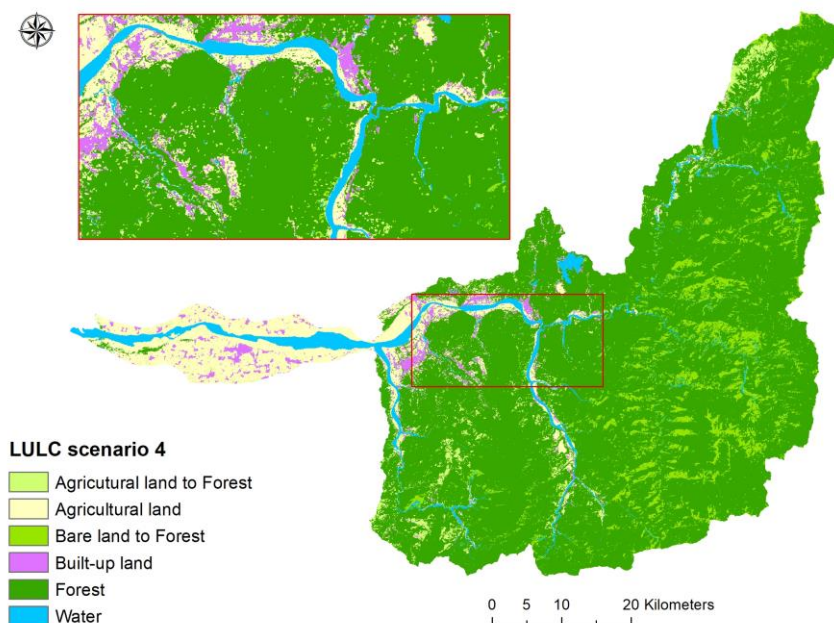


Figure 58. LULC scenario 4

Table 34. Summarizing LULC transformation matrix for scenario 2,3,4.

Scenario 2							
LULC	Original area (%)	Agri land	Bare land	Forest	Built-up land	Water	Projected area (%)
Agri land	11.43		0	0.80	0	0	45.87
Bare land	6.65	1.63		5.02	0	0	0.00
Forest	76.03	33.61	0		0	0	48.24
Built-up land	1.95	0	0	0		0	1.95
Water	3.94	0	0	0	0		3.94
Scenario 3							
LULC	Original area (%)	Agri land	Bare land	Forest	Built-up land	Water	Projected area (%)
Agri land	11.43		0	2.93	0	0	12.33
Bare land	6.65	0.21		6.44	0	0	0.00
Forest	76.03	3.62	0		0	0	81.78
Built-up land	1.95	0	0	0		0	1.95
Water	3.94	0	0	0	0		3.94
Scenario 4							
LULC	Original area (%)	Agri land	Bare land	Forest	Built-up land	Water	Projected area (%)
Agri land	11.43		0	2.93	0	0	8.50
Bare land	6.65	0		6.65	0	0	0.00
Forest	76.03	0	0		0	0	85.61
Built-up land	1.95	0	0	0		0	1.95
Water	3.94	0	0	0	0		3.94

3.2.16 Discussion and Conclusion of Work Package 4

3.2.16.1 Discussion:

In this study, LULC scenarios based on SLCC adapted from SWCB in Taiwan only consider physical conditions of soil, while land use planning might be significantly governed by socio-economic conditions, as well as political issues. However, the slope land capability unit represents the allowable land use of hilly areas. It provides effective information for the planners or farmers to adjust the current land use or to apply further measurement for the soil erosion control.

This study set the threshold of $100 \text{ t ha}^{-1} \text{ yr}^{-1}$ respective to a severe soil erosion as an input for SLCC. In the study area, bare land can be akin to water erosion scars on steep hilly slopes, and SLCC at Class V with soil severe rate over $100 \text{ t ha}^{-1} \text{ yr}^{-1}$ accounting for 75.45% of total bare land. Hence, this threshold can express the ability of severe soil erosion occurrence in reality. However, this threshold must be still further considered for improvement of SLCC, although some previous studies also used this threshold for soil severity erosion classification. Moreover, with rugged terrain conditions, if we only consider the slope gradient, soil depth and severe soil erosion, this may deal with some constraints in utilizing the slopeland capability class. We should take landform into account, because it can represent accessibility to slopeland capability units. For example, foot slope areas is easier to go for cultivations than ridge areas, even though these ridge sites may suffer from water erosion less than foot slope sites.

3.2.16.2. Conclusions:

The RUSLE model can support the establishment of LULC scenarios by SLCC modified from SWCB in Taiwan at the Zhoushui River Basin. It allows us to identify the spatial distribution of severe soil erosion, then integrate slope gradient and soil depth information into mapping SLCC with 5 classes prespective to various purposes at catchment scale. After that, the current LULC (2019) and SLCC will be considered to develop LULC scenarios for different objectives. It is obvious that among LULC scenarios, often the advantages and disadvantages come from diversified angles. Therefore, to design the most suitable LULC scenarios, it is needed to interrogate among land-use stakeholders to finalize the land use planning.

Besides the current LULC (scenario 1), three LULC transformations were proposed for their adjustments, following SLCC (scenario 2), trade-off between agricultural development and eco-environmental protection (scenario 3), and eco-environmental priority (scenario 4). In fact, built-up land and water body seem to be impractically converted to other purposes, so LULC scenarios only concern about the LULC transformation among agricultural land, forest and bare land.

Among these LULC strategies, the strategy 2 will remarkably make agricultural

land increase to 45.87% of the total area, and forest decreases to 48.24% of the total area. Consequently, strategy 2 will expand the agricultural activities, but forest reduction will also cause negative impacts on environment, such as soil erosion, landslide, sediment deposition, etc. In contrast, strategy 3 will slightly result in agricultural land increase by 1.0%, while forest area will sharply rise to 81.78% (an increase of 5.75%). Besides, strategy 4 for eco-environmental objective will lead agricultural land decline to 8.5% (decrease of around 3%), but forest will achieve the highest coverage at 85.61% of the total area due to LULC conversion from the whole bare land, and agricultural land of Class IV-V.

These LULC scenarios will provide alternative choices for local authorities or stakeholders in optimizing the utilization of land resources with the Zhuoshui River Basin.

Chapter 4 Conclusions and Suggestions

4.1 Conclusions

With the application of GIS and remote sensing techniques, the project analyzed the LULC change and soil erosion response to the LULC dynamics. This study employed Landsat images and the random forest algorithm to classify LULC for the years 2019, 2011 and 2005. We defined five different LULC types in the Zhuoshui River Basin that seemed to be quite stable or just fluctuated in a narrow range value. The study area maintains a large area of forest coverage with over 75% of the total area, while agricultural land accounts for around 12%. Bare land was primarily dominated and distributed mainly on steep slope land due to landslide or debris flows (over 6%). Although, built-up land was increased during this period, it expanded at a low rate (1.14% in 2005 and 1.90% in 2019).

Unlike the other contributing factors of soil erosion, LULC is always unstable due to human activities that convert natural land into others. As a result, the soil erosion rate can be accelerated. This study applied the RUSLE model to stimulate soil erosion rate and then analyze its response to LULC change. Some empirical equations and antecedent studies for identifying the input of this model developed in Taiwan were considered to employ for modeling. The results estimated annual soil loss rate for the years 2019, 2011, and 2005 and classified into 5 severity soil erosion classes. From the results, it highlights that the soil erosion rate has been gradually reduced during this study period. In general, large areas were suffered from moderate and moderate severe classes with over 50% of the total, mild erosion accounting for over 15% and the remaining percentage falling into severe and very severe classes.

Although bare land only made up a small proportion of the total area (around 6%), but it shared a large amount of soil loss in total with the mean value of $396.58 \text{ t ha}^{-1} \text{ yr}^{-1}$ in 2019. This figure was approximately fourth times higher than forest ($102.84 \text{ t ha}^{-1} \text{ yr}^{-1}$) in 2019. As for agricultural lands, it highly suffered from soil erosion at the rate of around $22 - 32 \text{ t ha}^{-1} \text{ yr}^{-1}$ during this study period.

This study applied the RUSLE-SDR model to estimate the long-term SY in the

Zhuoshui River Basin, in which SDR derived from the empirical SDR equations in Taiwan. The SDR for each sub-basin extracted from its mainstream length and slope gradient of the mainstream bed, together with the RUSLE illustrates a better prediction of soil erosion and SY than those derived from the catchment size. The predicted annual SY accounting for all upper streams is about 246.06 (10^6 t yr^{-1}), and the difference between the predicted and observed SYs is 24.47%.

As for runoff estimation, this study applied the SCS-CN method to estimate surface runoff, and then analyze its relation to landslide occurrence. Result illustrates that there is a slight decrease in the surface runoff for the whole basin in the last 15 years and landslide occurrence mainly happened on the hilly slope with the surface runoff value over 3000 mm yr⁻¹.

This study adapted Slopeland Capability Classification (SLCC) for Taiwan, in which one input comes from the RUSLE result in 2019. LULC scenarios were based on the consideration between SLCC and LULC in 2019. Besides the current LULC (scenario 1), LULC adjustments were recommended for three types of LULC scenarios, including LULC transformations following SLCC (scenario 2), trade-off between agricultural development and eco-environmental protection (scenario 3), and eco-environmental priority (scenario 4). These LULC scenarios will provide alternative choices for local authorities or stakeholders in optimizing the utilization of land resources with the Zhuoshui River Basin.

4.2 Suggestions

The contents of this project cover a wide range of disciplines and also relates to huge amount of data. Therefore, this project has to deal with various constraints and limitations.

Firstly, due to the lack of detail information on the current soil map of Taiwan, it only presents soil types or soil order, while land use scenarios or planning at large scale needs much more detailed spatial information, such as soil texture, soil depth. Therefore, it is necessary to establish or improve soil map in more detail.

Secondly, LULC is a crucial information for any soil erosion and hydrological models, and land use planning. The LULC classification from Landsat images is still limited in identifying detailed LULC types. Thus, the LULC scenarios in this study basically used LULC from Landsat image classification. For further study, we can consider on using higher spatial resolution from other satellite images to achieve a more detailed LULC.

Thirdly, the Zhuoshui River Basin severely suffers from water erosion and sediment deposition. Due to its steep slope, heavy rainfall, and fragile soil to erosion forcing, the water erosion process in this basin is very complicated in comparison with the other basins. It may include various types of water erosion, such as landslide or mass movement on slope. In fact, eroded material that deposes on footslope from slope failures (landslide, or mass movement), and landslide or mass movement scars (like bare land) will accelerate soil erosion rate. However, these kinds of phenomenon are still challenging to quantify their spatial distribution and volume. Thus, further consideration on soil erosion and sediment estimation needs much more efforts in the future.

Finally, even though the Zhuoshui River Basin is mainly covered by forest area (over 75% of the total area), the rate of soil erosion is still very high. To reduce soil erosion and sediment yield, it requires both agronomic and engineering measures to control water erosion process. Particularly, further consideration on how to restore forest at landslide scars and stabilize slope lands is critical issues for watershed management in the future.

References

[1]C.-W. Chen *et al.*, "Sediment yield during typhoon events in relation to landslides, rainfall, and catchment areas in Taiwan," *Geomorphology*, vol. 303, pp. 540-548, 2018.

[2]C.-W. Kuo, C.-F. Chen, S.-C. Chen, T.-C. Yang, and C.-W. Chen, "Channel Planform Dynamics Monitoring and Channel Stability Assessment in Two Sediment-Rich Rivers in Taiwan," *Water*, vol. 9, no. 2, 2017.

[3]L. C. Chiang, Y. C. Wang, and C. J. Liao, "Spatiotemporal Variation of Sediment Export from Multiple Taiwan Watersheds," *Int J Environ Res Public Health*, vol. 16, no. 9, May 8 2019.

[4]J.-C. Fu, J.-H. Jang, C.-M. Huang, W.-Y. Lin, and C.-C. Yeh, "Cross-Analysis of Land and Runoff Variations in Response to Urbanization on Basin, Watershed, and City Scales with/without Green Infrastructures," *Water*, vol. 10, no. 2, 2018.

[5]S. J. Kao and J. D. Milliman, "Water and Sediment Discharge from Small Mountainous Rivers, Taiwan: The Roles of Lithology, Episodic Events, and Human Activities," *The Journal of Geology*, vol. 116, no. 5, pp. 431-448, 2008.

[6]P. T. Ghazvinei *et al.*, "Approaches for delineating landslide hazard areas using receiver operating characteristic in an advanced calibrating precision soil erosion model," *Natural Hazards and Earth System Sciences Discussions*, vol. 3, no. 10, pp. 6321-6349, 2015.

[7]C. Hung, G.-W. Lin, H.-L. Kuo, J.-M. Zhang, C.-W. Chen, and H. Chen, "Impact of an Extreme Typhoon Event on Subsequent Sediment Discharges and Rainfall-Driven Landslides in Affected Mountainous Regions of Taiwan," *Geofluids*, vol. 2018, pp. 1-11, 2018.

[8]H.-C. Chan, P.-A. Chen, and J.-T. Lee, "Rainfall-Induced Landslide Susceptibility Using a Rainfall–Runoff Model and Logistic Regression," *Water*, vol. 10, no. 10, 2018.

[9]C. Alewell, P. Borrelli, K. Meusburger, and P. Panagos, "Using the USLE: Chances, challenges and limitations of soil erosion modelling," *International Soil and Water Conservation*

Research, vol. 7, no. 3, pp. 203-225, 2019.

[10]B.-S. Lin, C.-K. Chen, K. Thomas, C.-K. Hsu, and H.-C. Ho, "Improvement of the K-Factor of USLE and Soil Erosion Estimation in Shihmen Reservoir Watershed," *Sustainability*, vol. 11, no. 2, 2019.

[11]P. Panagos, P. Borrelli, K. Meusburger, C. Alewell, E. Lugato, and L. Montanarella, "Estimating the soil erosion cover-management factor at the European scale," *Land Use Policy*, vol. 48, pp. 38-50, 2015.

[12]Z. Tan, L. R. Leung, H. Y. Li, and T. Tesfa, "Modeling Sediment Yield in Land Surface and Earth System Models: Model Comparison, Development, and Evaluation," *Journal of Advances in Modeling Earth Systems*, vol. 10, no. 9, pp. 2192-2213, 2018.

[13]A. N. Khosla, *Silting of reservoirs*. Government of India Press, 1953.

[14]R. J. Garde and U. Kothyarl, "Sediment yield estimation," *Water and Energy International*, vol. 44, no. 3, pp. 97-123, 1987.

[15]E. M. Flaxman, "Predicting sediment yield in western USA," *Journal of the Hydraulics Division*, vol. 98, no. Hy 12, 1972.

[16]S. a. W. C. Bureau, "General&Basic Investigation and Analysis," 2019.

[17]S. K. Mishra, V. P. Singh, and P. K. Singh, "Revisiting the Soil Conservation Service Curve Number Method," in *Hydrologic Modeling*(Water Science and Technology Library, 2018, pp. 667-693.

[18]S. Mandal and R. Maiti, "Surface Run-off, Soil Erosion and Slope Instability," in *Semi-quantitative Approaches for Landslide Assessment and Prediction*, 2015, pp. 123-144.

[19]L.-C. Chan and F.-Y. City, "Slopeland capability classification as a tool in land use planning: A. Taiwan," *Ext. Bull. Food Fertilizer Technol. Center*, vol. 483, pp. 1-7, 2000.

[20]J. A. B. Pall Oskar Gislason, and Johannes R. Sveinsson, "Random Forest Classification of Multisource Remote Sensing and Geographic Data," *IEEE*, 2004.

[21]C. B. Colman *et al.*, "Different approaches to estimate the

sediment yield in a tropical watershed," *Rbrh*, vol. 23, no. 0, 2018.

[22]W.-C. Chou, "Modelling Watershed Scale Soil Loss Prediction and Sediment Yield Estimation," *Water Resources Management*, vol. 24, no. 10, pp. 2075-2090, 2009.

[23]C. G. Karydas, P. Panagos, and I. Z. Gitas, "A classification of water erosion models according to their geospatial characteristics," *International Journal of Digital Earth*, vol. 7, no. 3, pp. 229-250, 2012.

[24]J. M. Laflen and D. C. Flanagan, "The development of US soil erosion prediction and modeling," *International Soil and Water Conservation Research*, vol. 1, no. 2, pp. 1-11, 2013.

[25]K. G. Renard, *Predicting soil erosion by water: a guide to conservation planning with the Revised Universal Soil Loss Equation (RUSLE)*. United States Government Printing, 1997.

[26]B. S. Lin, K. Thomas, C. K. Chen, and H. C. Ho, "Evaluation of soil erosion risk for watershed management in Shenmu watershed, central Taiwan using USLE model parameters," *Paddy and Water Environment*, vol. 14, no. 1, pp. 19-43, 2015.

[27]D. L. D. Panditharathne, N. S. Abeysingha, K. G. S. Nirmanee, and A. Mallawatantri, "Application of Revised Universal Soil Loss Equation (Rusle) Model to Assess Soil Erosion in "Kalu Ganga" River Basin in Sri Lanka," *Applied and Environmental Soil Science*, vol. 2019, pp. 1-15, 2019.

[28]R. Benavidez, B. Jackson, D. Maxwell, and K. Norton, "A review of the (Revised) Universal Soil Loss Equation ((R)USLE): with a view to increasing its global applicability and improving soil loss estimates," *Hydrology and Earth System Sciences*, vol. 22, no. 11, pp. 6059-6086, 2018.

[29]J. Williams, K. Renard, and P. Dyke, "EPIC: A new method for assessing erosion's effect on soil productivity," *Journal of Soil and water Conservation*, vol. 38, no. 5, pp. 381-383, 1983.

[30]W. P. David, "Soil and water conservation planning: policy issues and recommendations," Philippine Institute for Development Studies 1988.

[31]S. El-Swaify, C. Gramier, and A. Lo, "Recent advances in

soil conservation in steep land in humid tropics," in *Proceedings of the international conference on steep land agriculture in the humid tropics*. Kuala Lumpur, MARDI, 1987, pp. 87-100.

[32]P. Panagos, P. Borrelli, and K. Meusburger, "A New European Slope Length and Steepness Factor (LS-Factor) for Modeling Soil Erosion by Water," *Geosciences*, vol. 5, no. 2, pp. 117-126, 2015.

[33]P. J. J. D. a. G. Govers, "A GIS procedure for automatically calculating the USLE LS factor on topographically complex landscape units," *Soil and Water Conservation*, vol. 51, pp. 427-433, 1996.

[34]P. Desmet and G. Govers, "Comment on 'Modelling topographic potential for erosion and deposition using GIS'," *International Journal of Geographical Information Science*, vol. 11, no. 6, pp. 603-610, 1997.

[35]A. Almagro *et al.*, "Improving cover and management factor (C-factor) estimation using remote sensing approaches for tropical regions," *International Soil and Water Conservation Research*, vol. 7, no. 4, pp. 325-334, 2019.

[36]V. Durigon, D. Carvalho, M. Antunes, P. Oliveira, and M. Fernandes, "NDVI time series for monitoring RUSLE cover management factor in a tropical watershed," *International Journal of Remote Sensing*, vol. 35, no. 2, pp. 441-453, 2014.

[37]J. Van der Knijff, R. Jones, and L. Montanarella, *Soil erosion risk assessment in Italy*. Citeseer, 1999.

[38]J. R. Dymond and J. D. Shepherd, "Correction of the topographic effect in remote sensing," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 37, no. 5, pp. 2618-2619, 1999.

[39]K. Ghosal and S. Das Bhattacharya, "A Review of RUSLE Model," *Journal of the Indian Society of Remote Sensing*, vol. 48, no. 4, pp. 689-707, 2020.

[40]V. Ferro and M. Minacapilli, "Sediment delivery processes at basin scale," *Hydrological Sciences Journal*, vol. 40, no. 6, pp. 703-717, 1995.

[41]D. E. Walling, "The sediment delivery problem," *Journal*

of hydrology, vol. 65, no. 1-3, pp. 209-237, 1983.

[42]L. Wu, X. Liu, and X.-y. Ma, "Research progress on the watershed sediment delivery ratio," *International Journal of Environmental Studies*, vol. 75, no. 4, pp. 565-579, 2017.

[43]S. Dutta, "Soil erosion, sediment yield and sedimentation of reservoir: a review," *Modeling Earth Systems and Environment*, vol. 2, no. 3, 2016.

[44]N. S. Magesh and N. Chandrasekar, "Assessment of soil erosion and sediment yield in the Tamiraparani sub-basin, South India, using an automated RUSLE-SY model," *Environmental Earth Sciences*, vol. 75, no. 16, 2016.

[45]W.-T. L. Chao-Yuan Lin, Wen-Chieh Chou, "Soil erosion prediction and sediment yield estimation: the Taiwan experience," *Soil & Tillage Research*, vol. 68, pp. 143-152, 2002.

[46]M. K. Jain and U. C. Kothyari, "Estimation of soil erosion and sediment yield using GIS," *Hydrological Sciences Journal*, vol. 45, no. 5, pp. 771-786, 2000.

[47]C. Hung, G.-W. Lin, H.-L. Kuo, J.-M. Zhang, C.-W. Chen, and H. Chen, "Impact of an Extreme Typhoon Event on Subsequent Sediment Discharges and Rainfall-Driven Landslides in Affected Mountainous Regions of Taiwan," *Geofluids*, vol. 2018, 2018.

[48]K. H. Ahn and S. Steinschneider, "Time-varying suspended sediment-discharge rating curves to estimate climate impacts on fluvial sediment transport," *Hydrological Processes*, vol. 32, no. 1, pp. 102-117, 2018.

[49]S.-J. Kao, S.-C. Chan, C.-H. Kuo, and K.-K. Liu, "Transport-dominated sediment loading in Taiwanese rivers: a case study from the Ma-an Stream," *The Journal of geology*, vol. 113, no. 2, pp. 217-225, 2005.

[50]F. Turkelboom, "On-Farm Diagnosis on Steepland Erosion in Northern Thailand: Integrating Spatial Scales with Household Strategies," Katholieke Universiteit Leuven, 1999.

[51]D. N. Kimaro, J. Poesen, B. M. Msanya, and J. A. Deckers, "Magnitude of soil erosion on the northern slope of the Uluguru Mountains, Tanzania: Interrill and rill erosion," *Catena*,

vol. 75, no. 1, pp. 38-44, 2008.

[52]D. N. Moriasi, J. G. Arnold, M. W. V. Liew, R. L. Bingner, R. D. Harmel, and T. L. Veith, "Model Evaluation Guidelines for Systematic Quantification of Accuracy in Watershed Simulations," *Transactions of the ASABE*, vol. 50, no. 3, pp. 885-900, 2007.

[53]A. S. Donigian, "Watershed Model Calibration and Validation: The Hspf Experience," *Proceedings of the Water Environment Federation*, vol. 2002, no. 8, pp. 44-73, 2002.

[54]H. Sverdrup, P. Warfvinge, L. Blake, and K. Goulding, "Modelling recent and historic soil data from the Rothamsted Experimental Station, UK using SAFE," *Agriculture, ecosystems & environment*, vol. 53, no. 2, pp. 161-177, 1995.

[55]O. Cerdan *et al.*, "Rates and spatial variations of soil erosion in Europe: a study based on erosion plot data," *Geomorphology*, vol. 122, no. 1-2, pp. 167-177, 2010.

[56]R. Morgan, "Soil erosion and conservation (ed.)," *Australia: Blackwell Science Ltd.(p16)*, 2005.

[57]V. G. Sterk, "Empirical water erosion modelling for soil and water conservation planning at catchment-scale," *Transactions on Ecology and the Environment*, vol. 46, 2001.

[58]J. de Vente *et al.*, "Predicting soil erosion and sediment yield at regional scales: Where do we stand?," *Earth-Science Reviews*, vol. 127, pp. 16-29, 2013.

[59]U. NRCS, "Urban Hydrology for Small Watersheds TR-55," *USDA Natural Resource Conservation Service Conservation Engineering Division, Technical Release*, vol. 55, p. 164, 1986.

[60]Z.-S. Chen, Z.-Y. Hseu, and C.-C. Tsai, *The soils of Taiwan*. Springer, 2015.

[61]J. L. LAXTON, "A Review of: "Geographic Information Systems for Geoscientists—Modelling with GIS" By GRAEME F. BONHAM-CARTER.(Kidlington: Pergamon, 1994). Pp. xvii+ 398. Price£ 27, 00/US 43.00Paperback,£70.00/US 110.00 Hardback," ed: Taylor & Francis, 1996.

[62]T. C. Sheng, "Watershed conservation," *Colorado State*

University, 1986.

[63]C. Perez and H. Tschinkel, *Improving watershed management in Developing Countries: A framework for prioritising Sites and practices*. London, England: Overseas Development Institute. Agricultural Research and ..., 2003.

[64]C. Wang, C. Shen, and L. Lin, "A Study on Rational Slope Land Classification and Use for Land Conservation in Taiwan," *Disaster advances*, vol. 5, no. 4, pp. 144-149, 2012.

[65]張庭瑜, 王湘閔, and 林昭遠, "陳有蘭溪集水區災後山坡地土地可利用限度查定快速評估之研究," *Journal of Chinese Soil and Water Conservation*, vol. 46, no. 3, pp. 158-170, 2015.

[66]K. Lo and C. Huang, "Appropriate land use planning for slope land in Taiwan," in *Soil Erosion*, 2001, p. 427: American Society of Agricultural and Biological Engineers.

[67]V. H. Durán Zuazo and C. R. Rodríguez Pleguezuelo, "Soil-erosion and runoff prevention by plant covers. A review," *Agronomy for Sustainable Development*, vol. 28, no. 1, pp. 65-86, 2008.

[68]R. V. O. Cruz, "Integrated land use planning and sustainable watershed management," in *Third Multi-Sectoral Watershed Management Forum*, 1997, pp. 27-28.

Research on assessment of soil erosion, runoff and establishment
of land use scenarios for soil-water conservation at Zhuoshui river basin

Appendix

Appendix1: Comments and Replies

項次	審查意見	回覆辦理情形
報告內容審查意見：		
一	How to choose the verification part and what is the result? Does it give any feedback to the original model?	In this study, verification is described below: - In the part of runoff simulation using SCS-CN model, we used the observed total runoff ($10^6 \text{ m}^3 \text{ yr}^{-1}$) from 6 stations to directly check with the predicted runoff. The results of validation is good enough to show the accuracy of the simulation performance. - In the coupled RUSLE-SRD model for sediment yield estimation, we also directly used the predicted sediment yield from each sub-basin to check with the measured sediment discharge at gauge station.
二	Through the empirical model, telemetry and GIS technology simulation, the contribution and innovation are worthy of recognition.	That is true. Thank to the development of advanced techniques in GIS and RS, it enables us to conduct our research more conveniently and more reliably.
三	The research results are rich and propose adjustment suggestions to preliminary policy plan. However, there is no further description of the practical	The comments are reasonable for the land use planning implementation. In fact, land use planning requires numerous steps, in which land suitability analysis is one of them. In the scope of this study, we only conduct the spatial analysis for the LULC adjustments based

項次	審查意見	回覆辦理情形
	application method. If the policy adjustment method and operation application can be explained more specifically, it will be more helpful for the presentation of research results.	on the adapted Slopeland Capability Classification in Taiwan. Then, we propose LULC transformations according to LULC scenarios that allow us to optimize the LULC utilizations within the Zhuoshui River Basin. From these LULC adjustments, decision makers can select the best option for the watershed management that is suitable with the local circumstance.
四	The influencing factors of RUSLE model include rainfall erosion index, soil erosion index, slope, slope length, vegetation cover, water and soil conservation treatment factors, etc. Each influencing factor has a high impact on soil erosion. This plan only focuses on the study of runoff and land use in soil erosion. It is recommended that the other factors are considered for overall consideration.	In this study, we already used the RUSLE model to quantify soil erosion rate. Its inputs include rainfall erodibility, soil erodibility, slope and slope length, vegetation cover and conservation practice. In fact, except for the LULC, the other factors are considered as unchanged inputs in the RUSLE. Thus, soil erosion change strongly depends on the LULC dynamics and its conservation practice. This is a reason why in this plan (LULC scenarios), we only focus on the LULC adjustments to reduce soil erosion rate.
五	It is helpful to provide evaluation and consideration of reasonable adjustment of land.	The reasonable adjustment of land is one of the crucial tasks that need to be implemented to support the watershed management.

項次	審查意見	回覆辦理情形
六	The research on soil and water conservation in the Zhuoshui River catchment area is complete and clear, and the implementation is highly completed.	We appreciate SWCB's consideration on the achievements of this project.

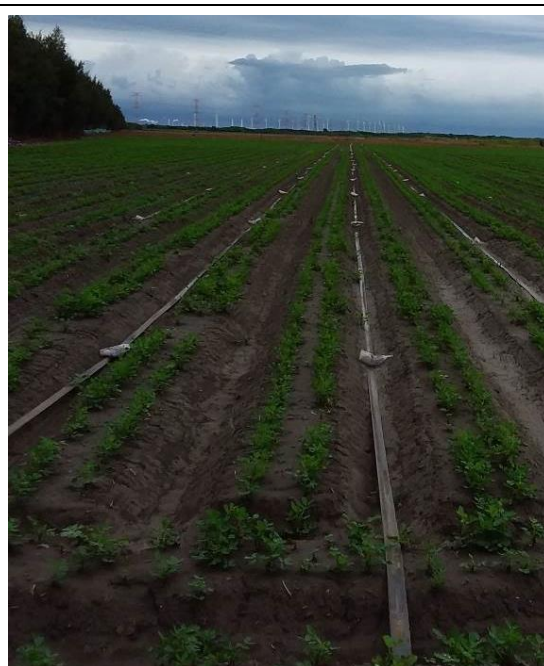
Research on assessment of soil erosion, runoff and establishment
of land use scenarios for soil-water conservation at Zhuoshui river basin

Appendix 2: Photos from field survey

Land use/land covers



Paddy field



Peanut field



Tea plantation

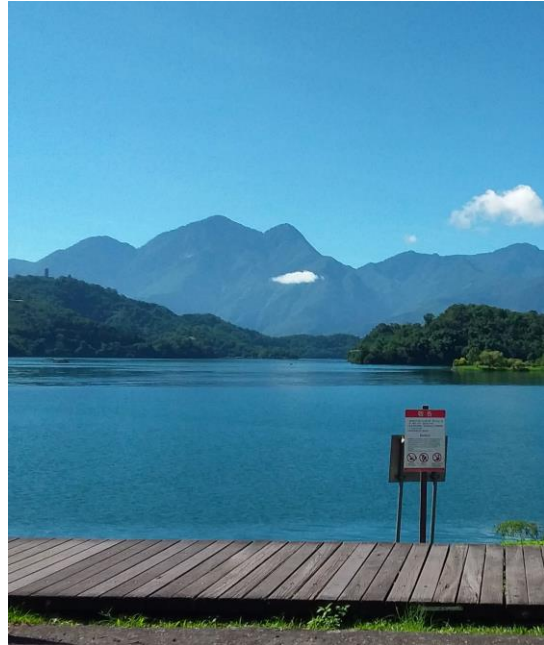


Watermelon

Research on assessment of soil erosion, runoff and establishment
of land use scenarios for soil-water conservation at Zhuoshui river basin



Built-up land



Water



Forest



Bareland (landslide scars)

Occurrences of soil erosion on slopeland



Sediment



Jiji weir

