Spatial modeling of soil erosion hazards and crop diversity change with rainfall variation in the Central Highlands of Sri Lanka

Sumudu Senanayake[1,2], Biswajeet Pradhan[1,3,4*], Alfredo Huete[1,5], Jane Brennan[1]

[1] The Centre for Advanced Modelling and Geospatial Information Systems (CAMGIS), Faculty of Engineering and IT, University of Technology Sydney, Sydney, 2007 NSW, Australia

[2] Natural Resources Management Centre, Department of Agriculture, Peradeniya, 20400, Sri Lanka.

[3.] Department of Energy and Mineral Resources Engineering, Sejong University, Choongmu-gwan, 209 Neungdong-ro, Gwangjin-gu, Seoul 05006, Korea

[4] Earth Observation Center, Institute of Climate Change, University Kebangsaan Malaysia, 43600 UKM, Bangi, Selangor, Malaysia

[5] Faculty of Science, University of Technology Sydney, Sydney, NSW 2007, Australia.

* Correspondence: Biswajeet.Pradhan@uts.edu.au; or biswajeet24@gmail.com

Abstract

The spatial variation of soil erosion is essential for farming system management and resilience development, specifically in the high climate hazard vulnerable tropical countries like Sri Lanka. This study aimed to investigate climate and human-induced soil erosion through spatial modeling. Remote sensing was used for spatial modelling to detect soil erosion, crop diversity, and rainfall variation. The study employed a time-series analysis of several variables such as rainfall, land-use land-cover (LULC) and crop diversity to detect the spatial variability of soil erosion in farming systems. Rain-use efficiency (RUE) and residual trend analysis (RESTREND) combined with a regression approach were applied to partition the soil erosion due to human and climate-induced land degradation. Results showed that soil erosion has increased from 9.08 Mg/ha/yr to 11.08 Mg/ha/yr from 2000 to 2019 in the Central Highlands of Sri Lanka. The average annual rainfall has increased in the western part of the Central Highlands, and soil erosion hazards such as landslides incidence also increased during this period. However, crop diversity has been decreasing in farming systems, namely wet zone low country (WL1a) and wet zone mid-country (WM1a), in the western part of the Central Highlands. The RUE and RESTREND analyses reveal climate-induced soil erosion is responsible for land degradation in these farming systems and is a threat to sustainable food production in the farming systems of the Central Highlands.

***Keywords*:** Soil erosion; rainfall variation; crop diversity change; remote sensing; GIS; Sri Lanka

1. Introduction

The global (macro and micro) climate variations inevitably influence agricultural food production. Tropical regions are more vulnerable in terms of reducing land productivity due to increasing temperature and monsoon rainfall variation (Borrelli et al., 2017). Scholars continuously struggle to understand the impact of climate change and to find solutions and adaptation measures to meet the growing food demand (Burrell et al., 2017; Panagos and Katsoyiannis, 2019). Lal (2011) emphasized that understanding the impact of climate change, vulnerability, and successful adaptation measures reduces the impact of unexpected events of climate variation. Similarly, modeling soil erosion and land-use change is important for predicting future impacts to take mitigation measures to secure food supply (Lal, 2011; Panagos and Katsoyiannis, 2019).

Human-induced climate and land-use changes greatly contribute to land degradation (Sivakumar, 2007; Lal, 2011; Borrelli and Panagos, 2020). As one of the land degradation types, water-related soil erosion in tropical farming systems reduces agricultural productivity and ecosystem services (Han et al., 2020). Irregular and intense precipitation induce water erosion (Puente et al., 2019). The above-ground vegetation cover with its deep root systems helps to reduce the run-off and mass soil movement and ultimately reduces gully erosion and landslides vulnerability (Vannoppen et al., 2015). This is an important point because, as Poesen (2018) points out, water erosion may induce environmental hazards such as gully erosion and landslides in tropical hillslopes.

Plant diversity enhances soil water storage capacity, reduces soil erosion, and improves other ecosystem services (Hou et al., 2016; Hunt et al., 2019). Plant diversity refers to the number of different plant species per land area unit and increases with the plant density and plant cover while improving the functional diversity (Wang et al., 2012). Hou et al. (2016) found that increasing plant diversity inhibits soil erosion under heterogeneous vegetation cover. Several other researchers also found that plant diversity has a substantial impact on soil erosion and helps to protect soil erosion (Pohl et al., 2009; Berendse et al., 2015; Liu et al. 2018).

In the tropical region, South Asian countries are highly vulnerable to soil erosion due to climate hazards such as drought, floods, and other extreme rainfall events (Lal, 2011). Sri Lanka ranked as the second country on the global climate risk index in 2019 (Eckstein et al., 2019). South Asian monsoonal rainfalls are varied with increasing sea surface temperatures (Ratna et al., 2021). The rainfall variation is emerging as a serious threat to national food production in Sri Lanka. There are major cropping seasons based on the monsoonal rainfall pattern in Sri Lanka. Evidence shows that the major economic crops such as tea and paddies are heavily impacted by these rainfall variations as 66% of total agricultural croplands are under rain-fed only(Esham and Garforth, 2013). A study by Hewawasam and Illangasinghe (2015), showed that rainfall variation heavily contributes to crop productivity losses and soil erosion in Sri Lanka. Further to this, rainfall variation and extreme events significantly increased soil erosion hazards such as gully erosion and landslides (Dang et al., 2019). Thus, the people and their livelihoods are highly vulnerable to the impact of climate change. The farming systems of Sri Lanka, particularly in the Central Highlands, are increasingly vulnerable to the adverse impact of climate change (Esham and Garforth, 2013).

Remote sensing data provides useful information to monitor long-term changes in ecosystems and agricultural land management for sustainable food production. Several studies investigated land degradation and plant diversity using various remote sensing technologies with time-series observation (Wessels et al., 2007; Burrell et al., 2017; Mondal et al., 2020). Remote sensing and geographical information system (GIS) have been widely applied to soil erosion and land-use change analysis (Senanayake et al., 2020a; Fenta et al., 2021). However, none of the studies attempted to employ spatial modeling of the soil erosion hazards and plant diversity change with respect to rainfall variation using time-series analysis with geo-informatics tools. Therefore, the specific objectives of this study were set to examine (i) soil erosion hazards and crop diversity changes; and (ii) the relationship between soil erosion hazard and rainfall variation in different farming systems of the Central Highlands in Sri Lanka. The current study provides a novel approach by integrating land-use and land-cover change, soil erosion hazards, crop diversity change and rainfall variation for early detection of soil erosion in the farming systems. This combined spatial modeling approach further enables the partitioning between human and climate-induced land degradation.

2. Study area

The Central Highlands of Sri Lanka is selected for this study as they are extremely vulnerable to soil erosion hazards, such as landslides and floods (Rathnayake et al., 2020; Ranasinghe et al., 2019). The central region of the country consists of hilly and mountainous terrain (Hewawasam et al., 2013). The total land area is about 10,618 km^2, and the land rises up to 2,500m above sea level. The western side of the region receives much higher rainfall (>2500 mm) than the eastern side (2500-1750 mm) (Rathnayake et al., 2020). The region has a high density of landslides distribution. Every year, landslides releases high quantities of sediments to the rivers, especially during the rainy season (Hewawasam, 2010). The Central Highlands has been declared as a protected area by the soil conservation act of Sri Lanka. Figure 1 shows the study area.

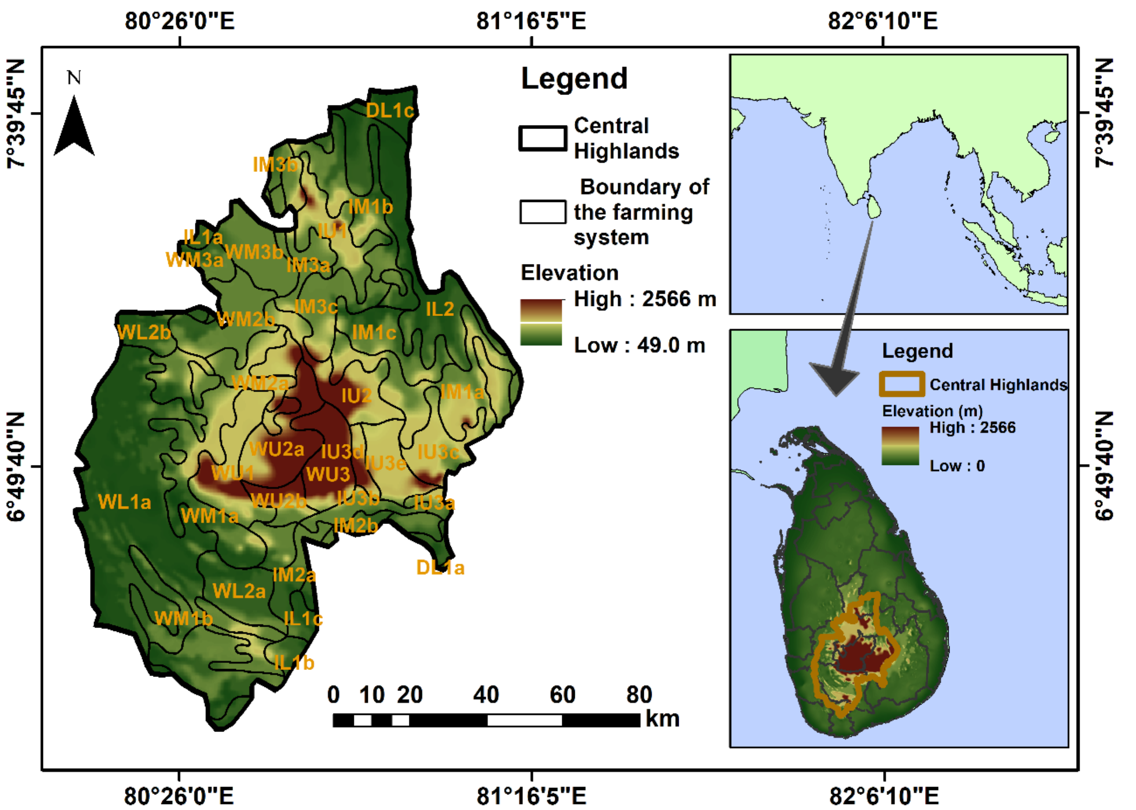


Figure 1. Location of the Central Highlands in Sri Lanka

3. Material and Methods

This study assessed the land-use and land-cover (LULC) change, the spatiotemporal distribution of soil erosion hazards, rainfall variation and crop diversity changes in farming systems of the Central Highlands. The main framework of this study encompassed four major assessments using spatial modeling techniques. The overall methodology of this study is shown in Figure 2. The agricultural (cropping) area under each agro-ecological region is considered as a farming system (Senanayake et al., 2021). There are 34 agro-ecological regions in the Central Highlands. The primary datasets, including satellite data (Landsat- LT 05, LE 07 and LC 08), precipitation data (satellite and gauge), topographic data, and landslides incidence from 2000 to 2019, were used in this study. Although Landsat is generally adequate for crop diversity analysis (Nagendra et al., 2010), cloud cover is one of the major limiting factors for this study area (Nay et al., 2018) especially to obtain bulk images throughout the year. Hence, atmospherically-corrected, Moderate Resolution Imaging Spectroradiometer (MODIS) product data (MOD13Q1) were used for crop diversity analysis. Data sources and spatial resolution can be found in Appendix A, Table A1 and A2.

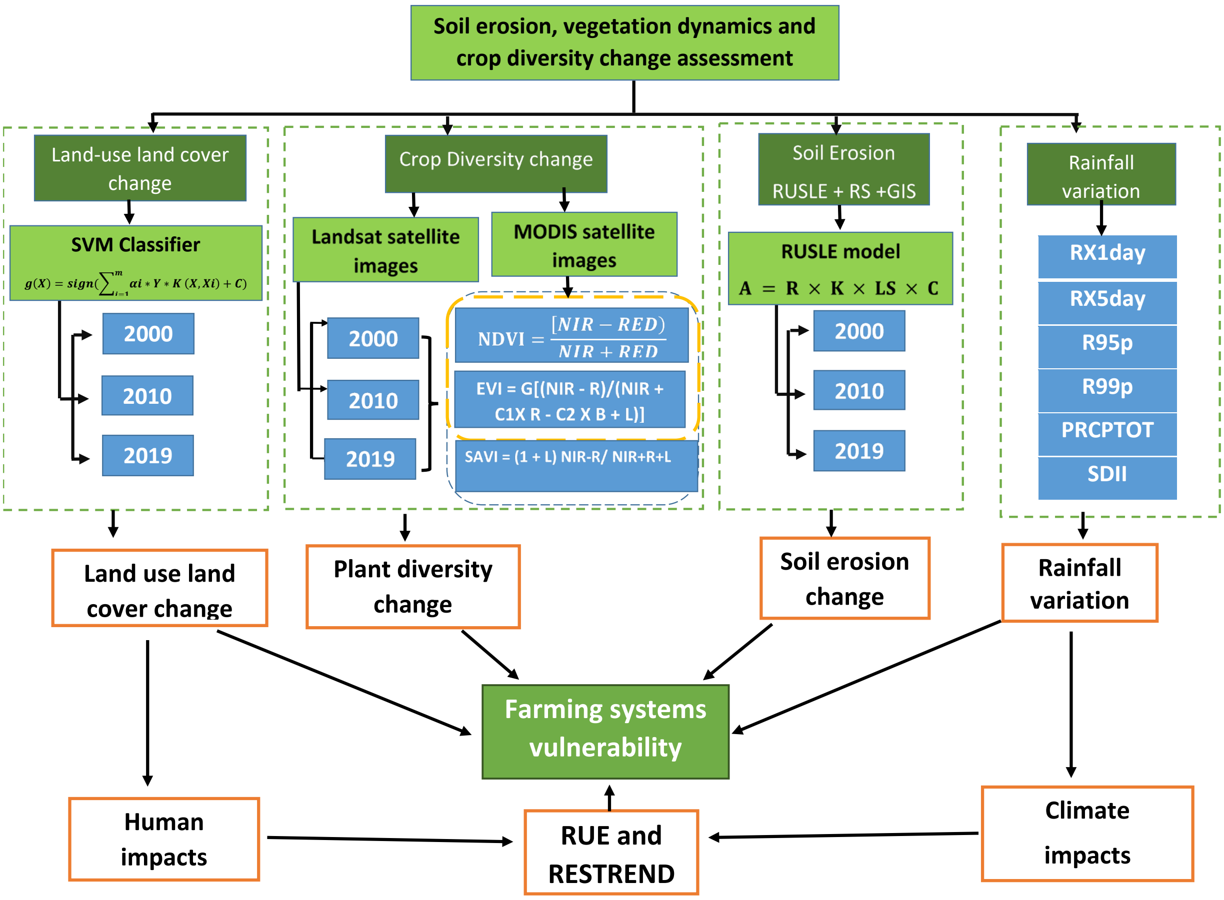


Figure 2. The flowchart of the methodology used for this study.

3.1 Land-use and land-cover change analysis

The landuse / landcover (LULC) classification was carried out through the support vector machine algorithm (SVM) using Landsat satellite images (Appendix A, Table A2) from 2000, 2010, and 2019. The SVM is a widely used machine-learning method (see Appendix B), introduced by Vladimir Vapnik and co-workers (Cortes and Vapnik, 1995). The Environment for Visualizing Images (ENVI) software was used for image processing. Each acquired image was geometrically corrected and registered into WGS 84 datum and UTM zone 44N projection. The radiometric and atmospheric corrections are prerequisites for generating high-quality images (Chander et al., 2009). The dark object subtraction method was applied to all images (Chavez, 1996) using the ENVI software. LULC time-series analyses were conducted after pan sharpening.

The land use maps were developed for 2000, 2010 and 2019. Six land-use classes were identified from the satellite images using land-use maps of the Land Use Policy Planning Department (LUPPD) of Sri Lanka. Olofsson et al. (2013) have highlighted the importance of accuracy assessment: user's, producer's and overall accuracy. Therefore, on average, 7500 training pixels were considered for each image to conduct a validation process using a confusion matrix. Finally, Kappa coefficients were derived for each classified image for 2000, 2010, and 2019. The Kappa coefficient is commonly used by researchers in accuracy assessment (Qi et al., 2012; Rizeei et al., 2016; Nampak et al., 2018).The Kappa coefficient is given in equation 1 (Bishop et al., 2007).

$$Kappa = \frac{N\sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r}(x_{i+})(x_{i+})}{N^2 - \sum_{i=1}^{r}(x_{i+})(x_{i+})} \qquad (1)$$

where, N is the total number of pixels of the ground truth (Singh et al., 2014) land-use classes, X_{ii} denotes the confusion matrix diagonals, $(x_{i+})(x_{i+})$ are the ground truth pixels in a class and the sum of the classified pixels in that class and the sum of overall classes.

3.2 Soil erosion assessment

The soil erosion vulnerability of each farming system in the Central Highlands was derived to find out the pattern of spatial and temporal variation of soil erosion. Although there are several approaches used to estimate soil erosion, a Revised Universal Soil Loss Equation (RUSLE) has been used in this study (see equation 2). The RUSLE method was used due to its easy integration of geo-informatics techniques as well as a practical method of considering a large land area and data-scarce situation. The RUSLE is a widely accepted attractive tool and has been used under different climatic conditions worldwide (Angima et al., 2003; Fernández and Vega, 2018; Alewell et al., 2019). This model has been successfully employed in several applications in tropical counties such as India, Sri Lanka (Ganasri and Ramesh, 2016; Senanayake et al., 2020b), and Malaysia (Nampak et al., 2018).

$$A = R \times K \times L \times S \times C \times P \qquad (2)$$

The annual soil loss per unit area (A) is given in tons per hectare per year. The rainfall erosivity factor (R) (MJ mm ha^{-1} $h^{-1}yr^{-1}$) was calculated with rainfall data from the past 30 years (1990-2019). The soil erodibility factor (K) (t ha h $MJ^{-1}mm^{-1}$), slope length and steepness factor (LS) (dimensionless), crop factor (C) (dimensionless) and conservation practices factor (P) (dimensionless) were derived from data gathered from different sources. A detailed description of this analysis is provided in Appendix C. The R, K, LS, C, and P factor layers were computed in 30m gridded raster format. The raster calculator tool in the spatial analysis was used to estimate the annual soil loss in the study area. The final soil erosion raster map was classified into five classes to identify the most vulnerable regions (Senanayake et al., 2020b). The soil erosion hazards maps were generated for 2000, 2010 and 2019.

3.3 Rainfall variation

Rainfall variation was analyzed to provide insight into the impact of climate variation on soil erosion. Rainfall data (ground-based) were collected from five agro-meteorological stations in the Central Highlands (Appendix E, Figure E1). The annual average of rainfall, rainfall anomaly and extreme indices such as maximum 1day precipitation, 95p, 99p (very and extremely wet days), the simple daily intensity index (SDII) and annual total wet day precipitation (PRCPTOT) were computed. Modified Mann-Kandall and Sen's slope tests (see Appendix E, Section E2) were employed to detect significant trends in precipitation indices using the R software for statistical analysis (McLeod and McLeod, 2014).

Moreover, the satellite rainfall dataset (PERSIANN-CDR) was downloaded from the Center for Hydrometeorology and Remote Sensing (CHRS) (https://chrsdata.eng.uci.edu/). Recent innovative trend analysis test (ITA) developed by Şen (2012), was also employed to evaluate the rainfall trends further (Şen, 2017). Satellite-based PERSIANN-CDR products matched well with the gauge-based precipitation in tropical regions (Sun et al., 2018). The CHRS data were used by many researches due to its capability of assessing rainfall trends(Baez-Villanueva et al., 2018; Sadeghi et al., 2021). A detailed description of this analysis is provided in Appendix E (section E3).

3.3.1 Rainfall variation and soil erosion hazards

Landslides are a good indicator of soil erosion hazards (Pradhan et al., 2012). Landslides inventory (Appendix F, Figure F2) was prepared using the disaster information system of the United Nations International Strategy for Disaster Reduction ‘Desinventar’ (UNISDR, 2021). The relationship between rainfall variation and soil erosion hazards was assessed using the landslides frequency ratio in each farming system. Landslide frequency ratio (FR) for each farming system can be estimated using equation (3) (Lee and Talib, 2005; Meena et al., 2019).

$$\mathrm{FR}_{(i)} = \frac{\mathrm{S}_{(\mathrm{i})}/\mathrm{A}_{(i)}}{\sum_1^n \left({S_{(i)}}/{A_{(i)}} \right)}\ , \qquad (3)$$

where, S_i the number of pixels containing landslides in class (i), A_i the total number of pixels in class (i).

3.3.2 Rainfall and vegetation indices

The MODIS data (MOD13Q1 - MODIS/Terra Vegetation Indices 16-Day) were downloaded (ORNL DAAC, 2018) from 2000 to 2019 and observed the relationship between NDVI and ground-based and satellite-based rainfall data. Pearson’s correlation coefficient was estimated between these two variables. Linear regression analysis was performed to estimate the coefficient of determination to identify respective trends of the NDVI. The coefficient of determination (R^2) was computed to find how much variability can be caused by its relationship to another related factor (Landmann and Dubovyk, 2014). In addition, the latest modified Kling-Gupta efficiency (KGE’) was used to test the goodness of fit (Appendix I). The results of the parameters were found to be consistent with the Pearson’s correlation coefficient (r), bias (beta), and variability ratio (gamma) (Gupta et al., 2009; Kling et al., 2012).

3.4 Crop diversity change analysis

Estimating plant diversity using remote sensing techniques has been conducted through direct and indirect methods (Turner et al., 2003; John et al., 2008). Direct methods are used with spectral reflectance values and various spatial resolutions from different sensors (Warren et al., 2014). Indirect methods have been derived from environmental parameters or biophysical characteristics, such as primary productivity or habitat structure, which are estimated from remote sensing techniques (Turner et al., 2003; John et al., 2008).

Plant diversity has been studied by many researchers using vegetation indices, such as NDVI and EVI (Waring et al., 2006; Levin et al., 2007; Chitale et al., 2019). Several researchers have reported that there is a strong relationship between plant species diversity with vegetation indices such as NDVI (Levin et al., 2007; Pouteau et al., 2018) and the enhanced vegetation index (EVI) (Waring et al., 2006; Morisette et al., 2006). Previous studies indicate that Landsat derived vegetation indices are highly sensitive to plant abundance and species richness in tropical landscapes (Nagendra et al., 2010). Nagendra et al. (2010) found that vegetation indices have low, non-significant relationships with stand density (the number of trees per unit area) and they also found stronger relationships with species richness and diversity. The standard deviation (SD) of the NDVI is positively correlated with total species richness and annual plant richness. Pau et al. (2012) found that NDVI values have increased by 30%- to 60% due to variance of tree species richness in a tropical forest (Pau et al., 2012). In addition, they established that NDVI was positively correlated with the tree cover, and NDVI values can be used to distinguish between dense forests and non-forested areas, such as agricultural fields and savannahs. NDVI values range from −1 and +1. NDVI values are above zero in vegetated areas and below zero can be assumed to be non-vegetated (Warren et al., 2014).

Many investigations have been conducted to identify the relationship associated with the EVI index and plant species richness (Waring et al., 2006; Morisette et al., 2006). There is a positive relationship between EVI and species richness. The EVI is independent of climate drivers (Waring et al., 2006). The EVI was developed to optimize the vegetation signal to improve vegetation monitoring by removing the background soil signal and atmospheric influences (Huete et al., 2002). The difference between the EVI and NDVI of MODIS satellite products is an adjustment for the atmosphere and soil background (Huete et al., 2002). Therefore, it is worth to note that NDVI and EVI can be used for mapping and predicting patterns of species richness in large areas. These applications are relatively low cost (Levin et al., 2007; Nagendra et al., 2010). In addition, researchers commonly use the soil adjusted vegetation index (SAVI) to investigate land degradation. SAVI minimizes the spectral variation caused by the soil background (Huete, 1988). The vegetation indices and the respective equations can be found below (Eq 4-6).

NDVI	$\mathrm{NDVI} = \frac{(NIR - RED)}{NIR + RED}$	(4)	(Rouse et al., 1974)

SAVI	$\text{SAVI} = \frac{(NIR - RED)(1 + L)}{NIR + RED + L}$	(5)	(Huete, 1988)
	Where L= correction factor between 0 and 1		
EVI	$\text{EVI} = G\frac{(NIR - RED)}{(NIR + C1.RED - C2.B + L)}$	(6)	(Liu and Huete, 1996)
	G = 2.5; C1 = 6; C2 = 7.5; L = 1		

This study examines the crop diversity change and soil erosion hazard using NDVI, EVI, and SAVI using multiple data sources. Yang et al. (2020) highlighted that using various data sources complements for the cross-validation of a study. Nagendra et al. (2010) claimed that Landsat imagery is more suitable for vegetation diversity assessment. They found medium-resolution Landsat ETM+ (30m) correlates stronger than high-resolution IKONOS imagery (4 m) with plant diversity in a dry tropical forest. Due to higher cloud cover around Sri Lanka throughout the year, trend analysis could not be carried out only with Landsat imageries. Hence, MODIS -250m 16 days' products (MODIS-MOD13Q1) were used for time series analysis for the years 2001–2019 (LPDAAC, 2021). The MODIS-derived variables have also shown the ability to predict plant species richness at the regional level (John et al., 2008). In addition, MODIS productivity estimates (NDVI/EVI/GPP) are readily available online and provide global coverage (Huete et al., 2002). The MODIS vegetation index products are generated by compositing daily data every 16 days, resulting in 23 composites per year and avoid cloud cover and other effects (Huete et al., 2002).

The Shannon diversity index is used to measure plant diversity (Nagendra, 2002). This diversity index produces an evaluation of landscape richness and evenness. It measures the number and the relative abundance or evenness of each species. A MODIS derived Shannon diversity index was used to evaluate the crop diversity during this period. The Shannon diversity index (SHDI) (Shannon, 1948) is given in equation (7).

$$\text{SHDI} = 1 - \sum_{\text{i}=1}^{\text{N}} P_i \times \text{In} P_i \qquad (7)$$

where, N is the number of land cover types, and Pi is the proportional abundance of the ith type (Nagendra, 2002). This index ranges in theory from 0 to infinity.

In this study, crop diversity changes were further assessed using the case study approach. Three case studies were conducted covering the Central Highlands to identify the crop diversity changes at the farming system level. The most vulnerable two farming systems (WL1a, WM1a) and moderate vulnerable farming system (IU3e) for soil erosion were identified based on the cropping area, soil erosion and number of landslides occurrence in the last two decades. The following criteria were used to select farming systems for the case studies (Appendix F, Figure F3): (i) the percentage of land area under high and very high soil erosion hazard classes; (ii) the number of landslides occurrence in the past two decades; and (iii) the agricultural area's vulnerability to soil erosion. The identified farming systems are given in Figure 3.

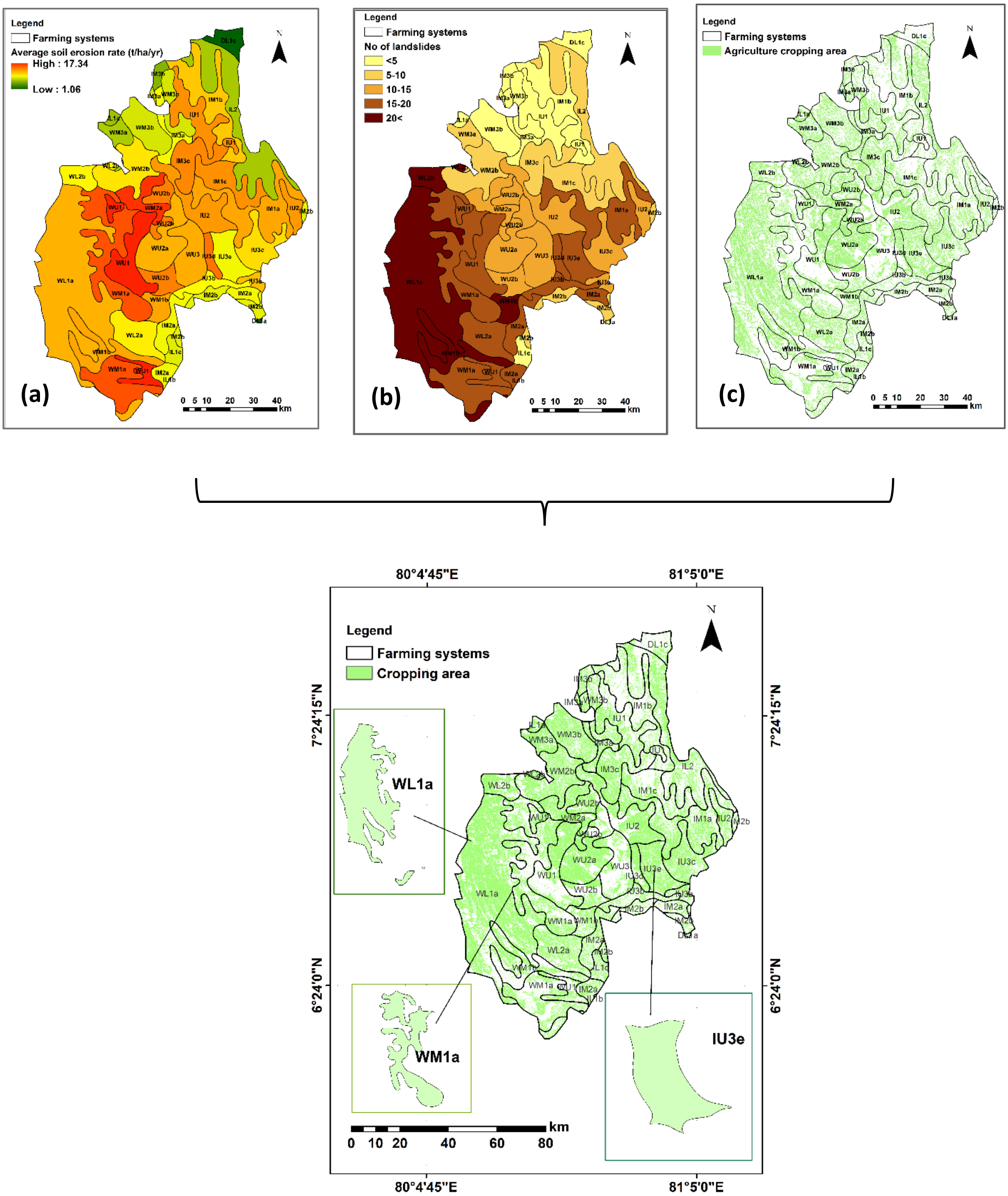


Figure 3. a) Average soil erosion rate, b) the number of landslides occurred, c) agricultural cropping area in the farming system, and d) selected farming systems for three case studies.

The Pearson's correlation coefficients (r) were computed to explore the relationship between vegetation indices values, plant species richness and diversity of disturbance types (Warren et al., 2014). Pearson's correlation coefficient provides correlation statistically as a measure of the strength of the linear relationships. Values that are closer to one indicate a stronger relationship or correlation. Statistical models were developed using the linear regression technique.

2.4.1 Vegetation indices and soil erosion

Many researchers have used vegetation indices to differentiate soil erosion/land degradation from climate change and anthropogenic activities. The Rain-use efficiency (RUE) and residual trend (RESTREND) indices are derived from vegetation indices (NDVI and EVI) to study land degradation (Wessels et al., 2012; Cunha et al., 2020). RUE and RESTREND analyses have been popularized for assessing the long-term changes in vegetation over the last few decades (Kundu et al., 2017). The following rule of thumb is applied: where vegetation dynamics are strongly driven by rainfall, declining RUE is correlated with land degradation. In humid areas, where vegetation is not as strongly driven by rainfall variation, the NDVI is strongly correlated with vegetation dynamics and may be taken as a proxy for land degradation (Yengoh et al., 2014).

2.4.2 Rain-use efficiency

Rain-use efficiency (RUE) can be used to normalize the effects of rainfall in vegetation productivity (Fensholt et al., 2013; Liu et al., 2015). The RUE is the ratio between the annual sum of vegetation productivity and annual rainfall (Wessels et al., 2012). Temporal change of RUE has been used to detect land degradation (Liu et al., 2015). Prince et al. (1998) highlighted that decreased RUE referred to land degradation by reduced vegetation coverage and increased run-off. The declining RUE is correlated with land degradation (Yengoh et al., 2014). RUE may vary with species distribution (Fensholt et al., 2013). However, some researchers still argue whether RUE is an effective indicator of land degradation (Wessels et al., 2007). The RUE can be derived from equation 8,

$$\mathrm{RUE} = \frac{\sum \mathrm{NDVI}}{\text{Average annual rainfall}} \qquad (8)$$

where, $\sum$NDVI is the average annual sum of NDVI.

2.4.3 Residual trend analysis

Residual trend analysis (RESTREND) was proposed by Evans and Geerken (2004). Predicted NDVI indicates the climatic impact on NDVI, whereas observed NDVI is the result of both climate and anthropogenic factors. A negative RESTREND indicates human-induced degradation of vegetation, and a positive RESTREND indicates the improvement of vegetation conditions (Kundu et al., 2017). RESTREND is obtained from the differences between the observed ∑NDVI and the ∑NDVI predicted by the rainfall using regressions calculated for each pixel. The equation for RESTREND is in equation 9 (Wessels et al., 2008; Wessels et al., 2012).

$$\mathrm{RESTREND} = \mathrm{observed} \sum \mathrm{NDVI} \; - \; \mathrm{predicted} \sum \mathrm{NDVI} \quad (9)$$

In this study, the RUE and RESTREND were employed using NDVI and EVI indices of MODIS data to find the impact of climate and human-induced soil erosion/land degradation. The time-series analysis of NDVI and EVI indices from 2000 to 2019 were used to derive RUE and RESTREND.

4. Results

4.1 Land-use and land-cover change

Land-use and land-cover (LULC) change analysis was carried out using Landsat imagery for 2000, 2010 and 2019 by employing the support vector classifier algorithm. The accuracy assessments indicate the Kappa coefficients: 0.83 in 2000, 0.81 in 2010 and 0.83 in 2019 (see Appendix D, Table D2- 4). Figure 4 shows the resulted classification maps for 2000, 2010 and 2019. Table 1 shows the respective findings of the analysis. The results indicate that dense forest and open forest have decreased during this period by 14.5% and 5.8%, respectively, while agricultural areas and built-up areas have increased by 15.4% and 2.35%.

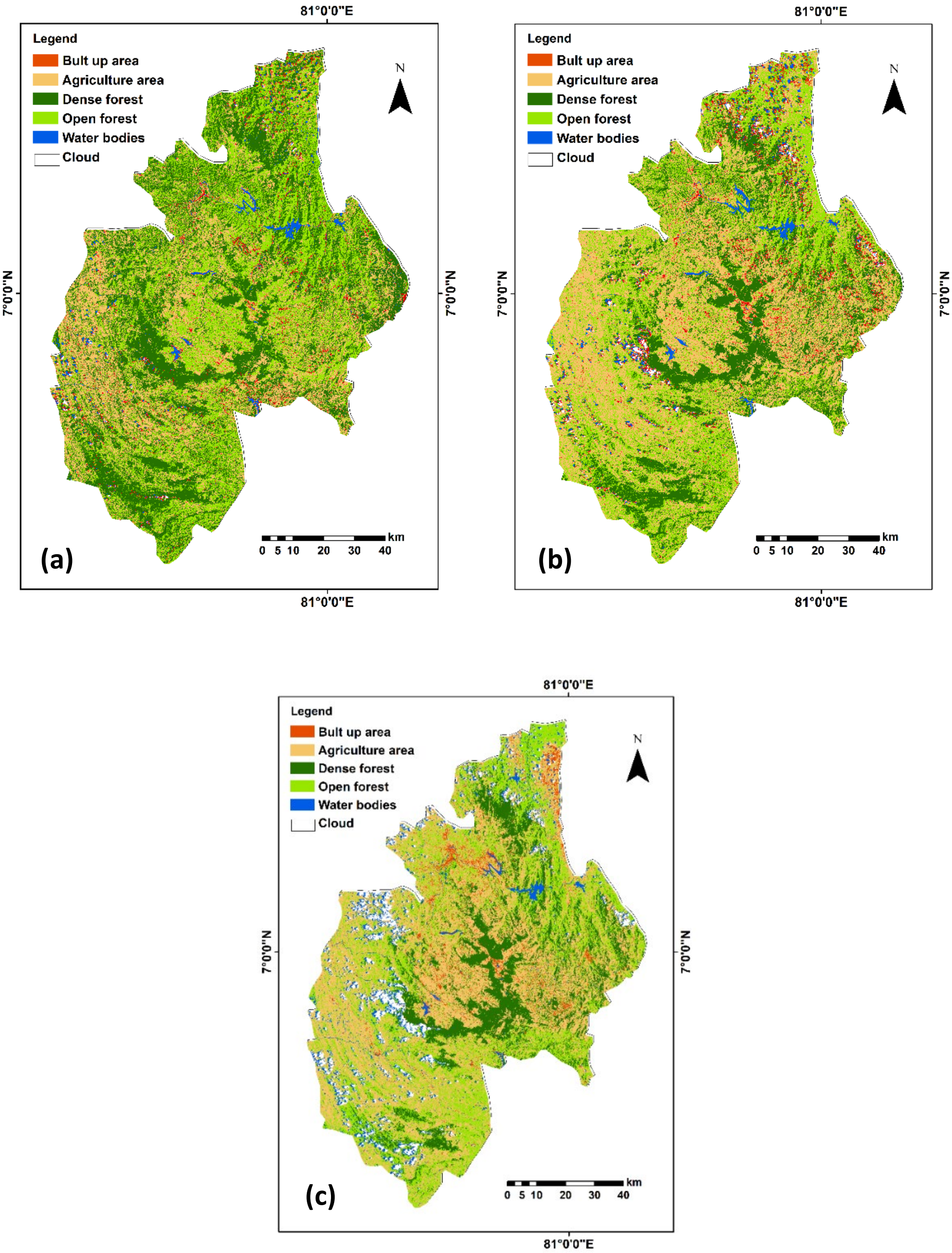


Figure 4. LULC maps in the Central Highlands: a) 2000, b) 2010, and c) 2019

Table 1. LULC change from 2000 to 2019

	Area (km^2)						
Classes	**2000**	%	**2010**	**%**	**2019**	**%**	**Change**
Dense Forest	3452.9	32.9	2491.9	23.7	1927.5	18.4	**-1525.4**
Open forest	3761.4	35.8	3391.6	32.3	3150.9	30.0	**-610.6**
Agriculture area	2718.3	25.9	3881.4	37.0	4333.2	41.3	**1614.9**
Built-up area	299.5	2.85	373.6	3.6	546.0	5.2	**246.5**
Water bodies	137.4	1.31	59.9	0.6	137.3	1.3	**-0.1**
Other (Cloud)	130.4	1.24	383.6	3.7	404.6	3.9	**274.2**
	10500.0	100.0	10500.0	100.0	10500.0	100.0	

4.2 Soil erosion hazards

The generated soil erosion hazards maps are illustrated in figure 5. The details of soil erosion hazard class distribution from 2000 to 2019 are given in Table 2 and Appendix C (Figure C3). According to the results of the study, soil erosion rates are increasing. The mean annual soil erosion rate was 9.08 Mg/ha/yr in 2000, and it increased to 10.17 Mg/ha/yr in 2010 and 11.08 Mg/ha/yr in 2019 (Table 2). The land areas under high and very high soil erosion classes were increased by 286.1km^2 and 166.3 km^2, respectively. The average soil erosion rate and landslide frequency ratio for each farming system were also assessed. The results are given in Appendix F, Table F1. The highest soil erosion rates can be observed in farming systems in the wet zone. This increasing soil erosion trend may be a result of the climate variation and anthropogenic impact of LULC change.

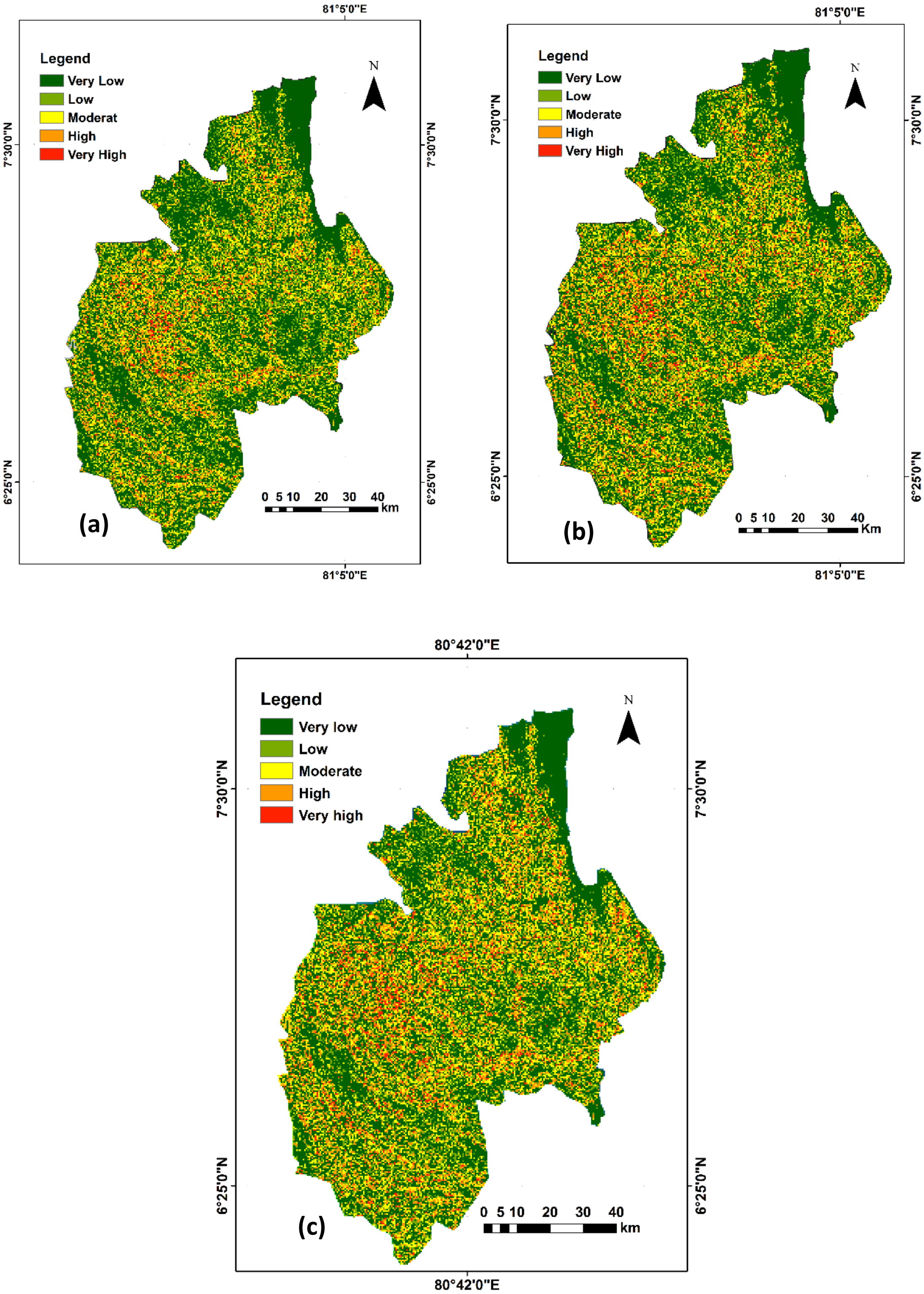


Figure 5. Soil erosion hazard map for: a) 2000, b) 2010, and c) 2019

Table 2. The details of soil erosion hazard classes, rates, and area distribution

Class	Soil erosion rate	Area (km^2)			Change
		2000	2010	2019	**2000 -2019**
Verylow	<5	5494.7	5345.6	5140.3	**-354.4**
Low	5-10	1733.3	1569.5	1555.3	**-178.1**
Moderate	10-20	1831.1	1847.4	1911.2	**80.2**
High	20-50	1221.2	1404.3	1507.3	**286.1**
Very high	50<	219.7	333.2	385.9	**166.3**
Total land		10500.0	10500.0	10500.0	
Average annual soil erosion (t/ha/yr)		**9.08**	**10.17**	**11.08**	

4.3 Rainfall variation

The increasing trend of average annual rainfall could be observed in all stations in the Central Highlands. According to table 3, satellite-based rainfall data show a significantly increasing trend in all the stations. Similarly, ground-based rainfall data also indicate significantly increasing rainfall except in Nuwara Eliya and Kundasale stations. Figure 6 illustrates the results of innovative trend analysis based on satellite rainfall data. Researchers have reported the increasing trend of average annual precipitation in Sri Lanka. Nearly 75% of meteorological stations have shown a significantly increasing trend (Jayawardena et al., 2018).

Table 3. Results for innovative trend test (slope *s*) of annual rainfall in the Central Highlands.

Station	Slope (s)	Trend indicate (r)	Standard deviation (σ)	Slope standard deviation (σs)	Level 90% Sig.	Level 95% Sig.	Level 99% Sig.	Type of trend
Satellite rainfall data								
Ratnapura	22.66**	0.98	317.45	1.61	±2.64	±3.14	±8.17	Increasing
Peradeniya	21.53**	1.18	281.64	2.48	±4.08	±4.86	±6.39	Increasing
Nuwaea Eliya	21.30**	1.03	300.21	2.68	±4.4	±5.24	±5.29	Increasing
Bandarawella	21.30**	1.03	300.21	2.68	±4.40	±5.24	±6.89	Increasing
Kundasale	21.53**	1.18	281.64	2.48	±4.08	±4.86	±6.39	Increasing
Ground-based rainfall data								
Ratnapura	35.53**	0.99	536.89	4.90	±8.60	±9.06	±12.62	Increasing
Peradeniya	22.90**	1.20	381.54	2.71	±4.46	±5.31	±6.99	Increasing
Nuwaea Eliya	3.40	0.20	381.89	3.99	±6.57	±7.83	±10.29	Increasing
Bandarawella	16.97**	1.02	310.07	4.77	±7.84	±9.35	±12.28	Increasing
Kundasale	5.20	0.36	343.97	3.17	±5.22	±6.22	±8.17	Increasing

* and ** represent 95% and 99% significance levels, respectively

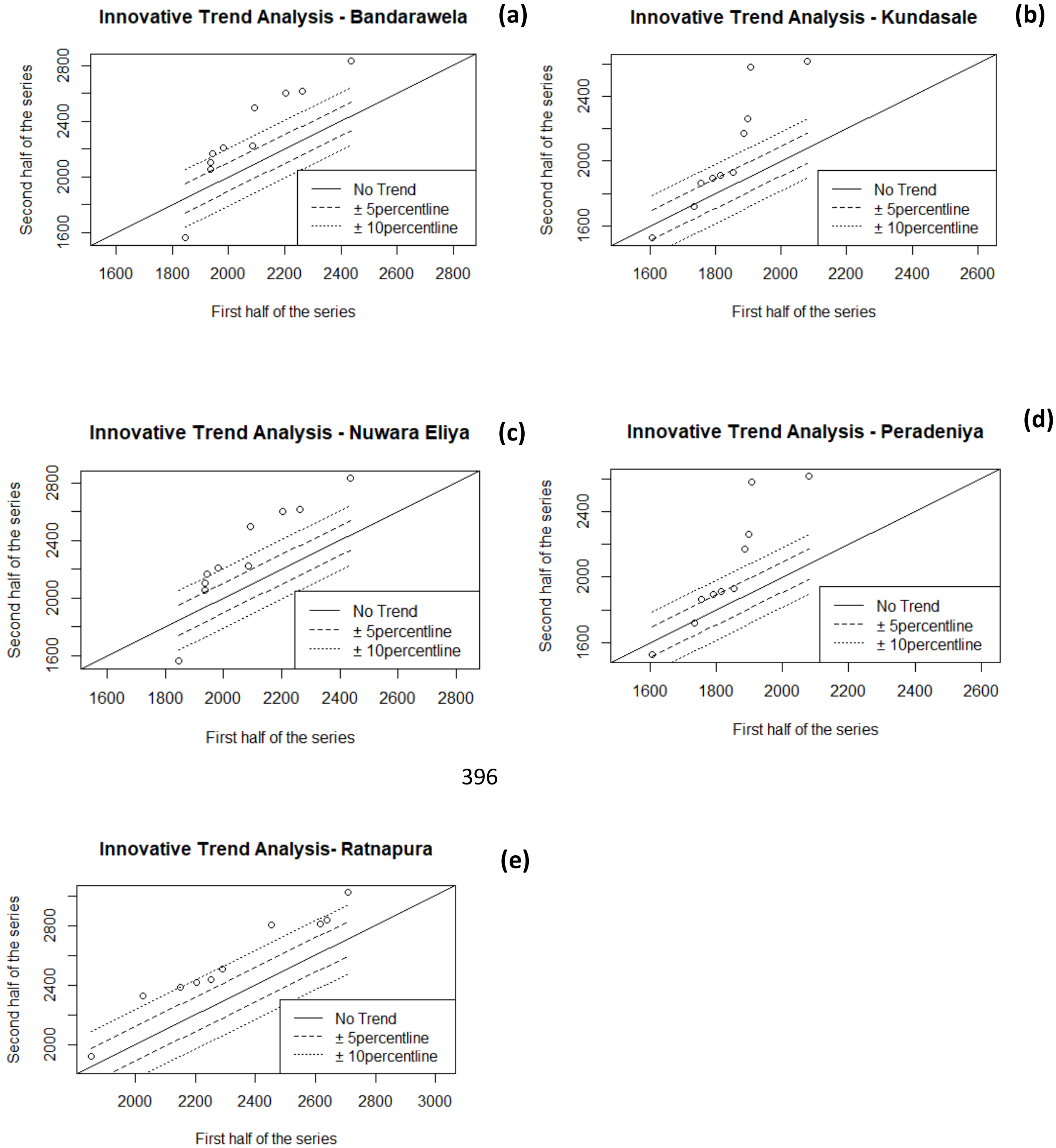
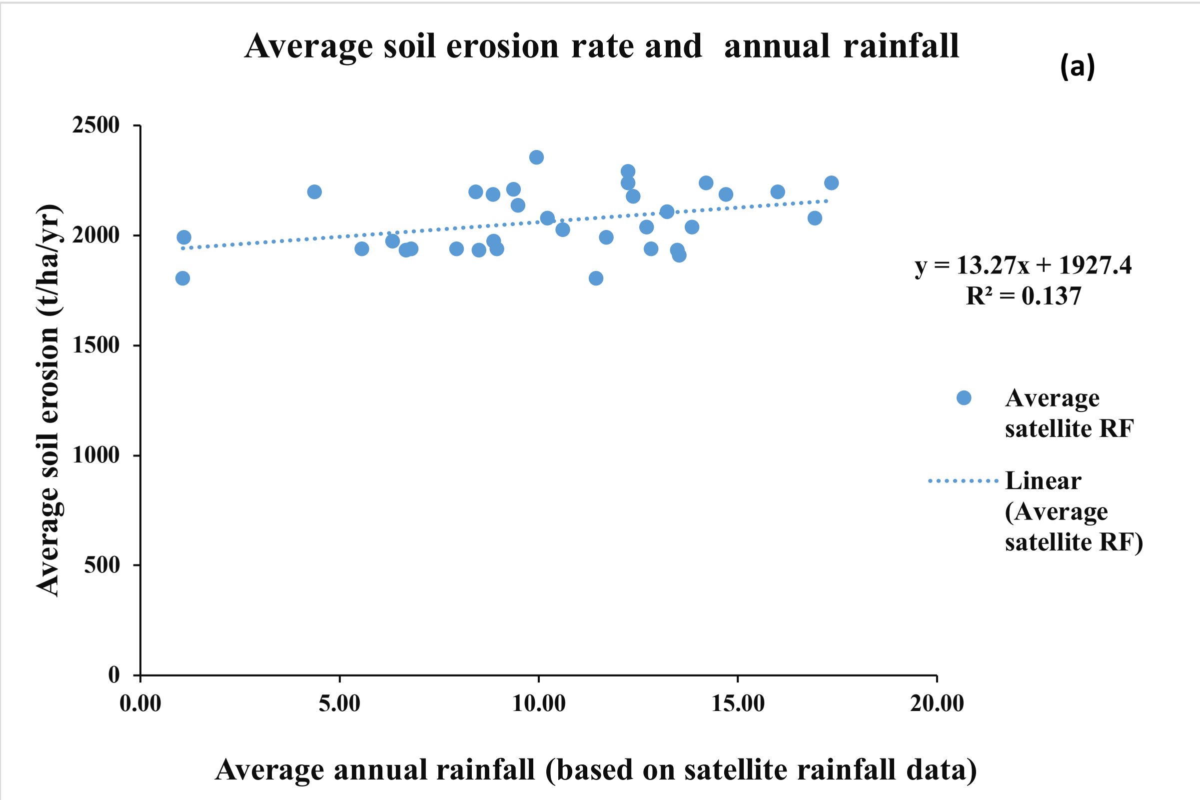


Figure 6. The Inovative trend analysis in (a) Bandarawela (b) Kundasale, (c) Nuwara Eliya (d) Peradeniya and (e)Ratnapura, stations from satellite-based rainfall data.

4.3.1 The relationship between rainfall variation and soil erosion hazards

Findings indicate that there are positive correlations between variables (Appendix I,Table I1): average annual rainfall and soil erosion rates r = 0.390 ($p<0.05$), landslides frequency ratio and average soil erosion rate r = 0.416 ($p<0.05$). The regression model in Figure 7 shows the relationships between soil erosion rate and average annual rainfall and average soil erosion rate and landslide frequency ratio in each farming system. Modified Kling–Gupta efficiency values are shown in table I2. Ranasinghe et al. (2019) highlighted that heavy and prolonged rainfalls are the main triggering factors for landslides in Sri Lanka. Rozos et al. (2013) argue that soil erosion could trigger landslides manifestation. Hence, the results of this study indicate that rainfall erosivity and soil erosion triggers the incidence of landslides in the Central Highlands. Hence, the results of this study indicate that rainfall erosivity and soil erosion triggers the incidence of landslides in the Central Highlands.



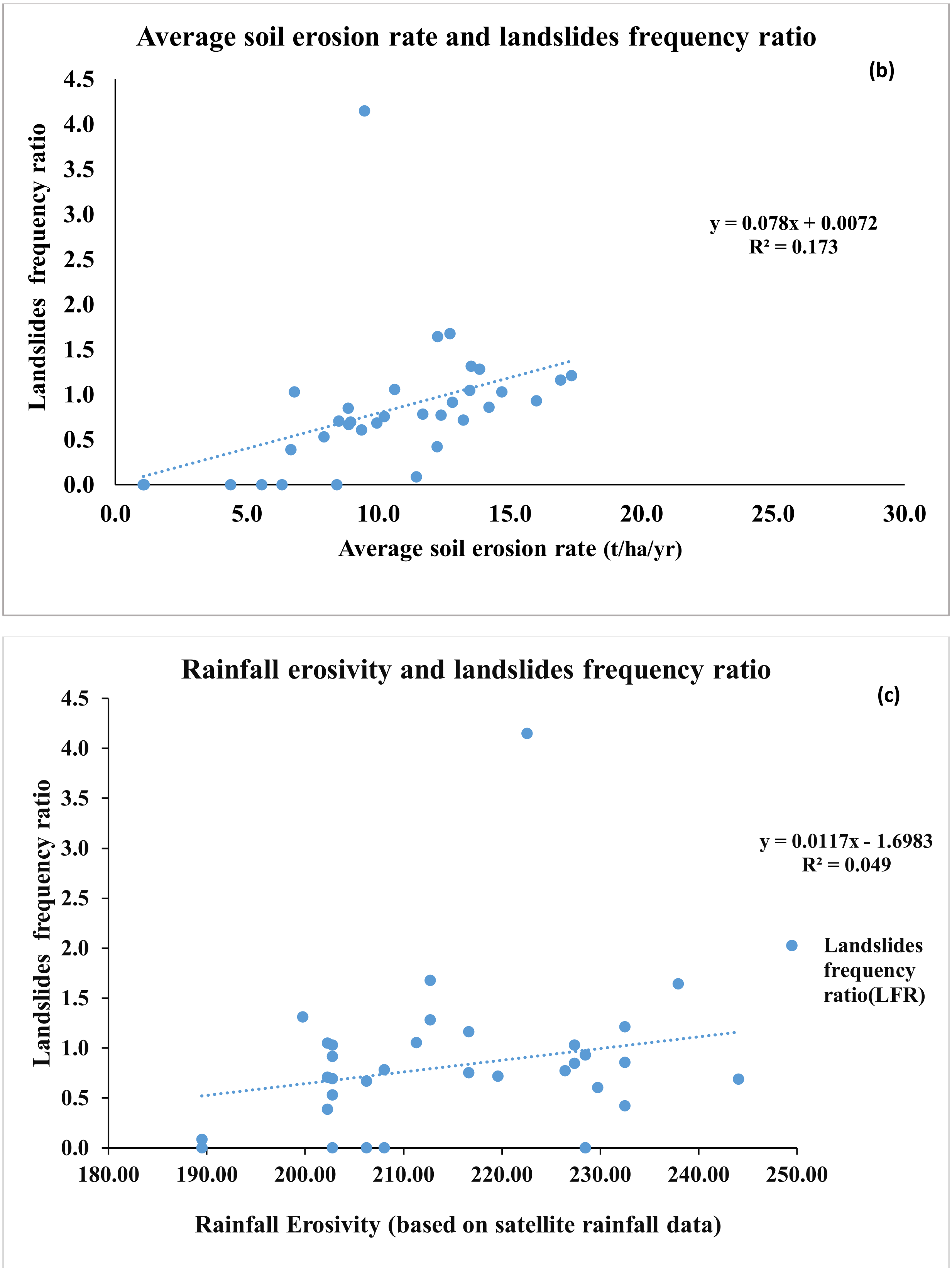
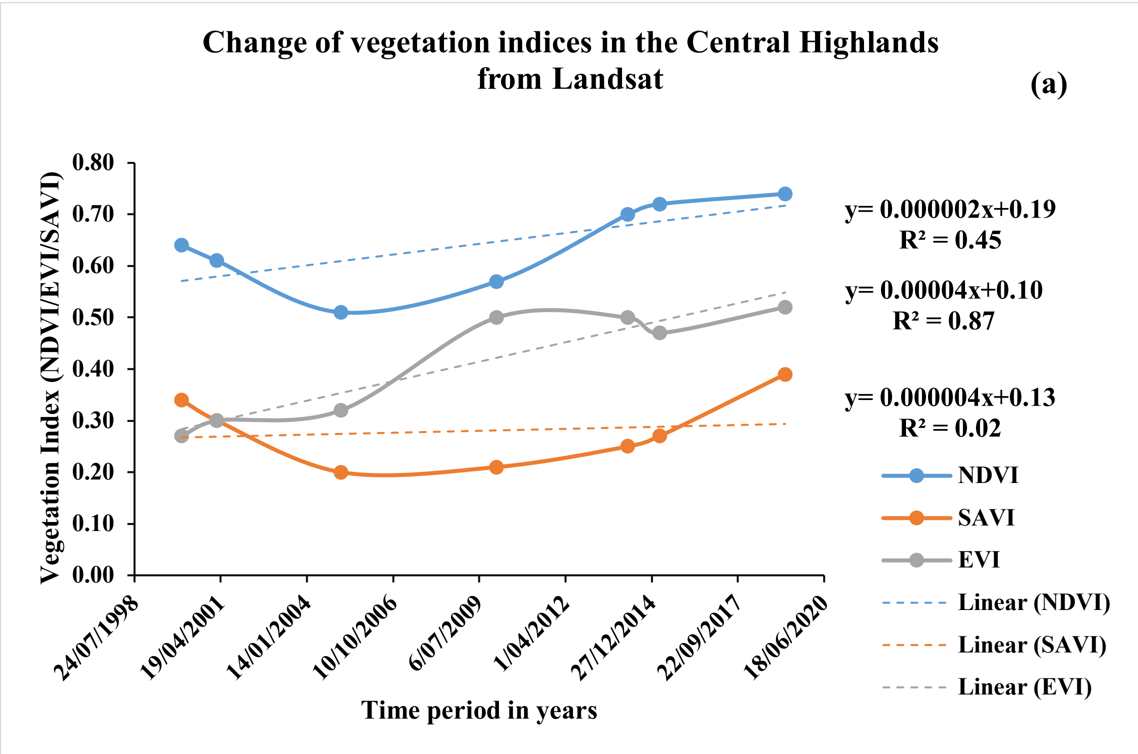


Figure 7. The details of the relationship between a) soil erosion and average annual rainfall b) average annual soil erosion rate and landslide frequency and (c) rainfall erosivity and landslides frequency ratio in each farming systems.

4.4 Crop diversity change in the farming systems

Based on the results of vegetation indices, the NDVI, EVI and SAVI show an overall increasing trend over the years. Figure 8 shows the distribution of vegetation indices over the period and respective images (Appendix G, Figure G1-3) derived from Landsat and MODIS imagery for the NDVI, EVI and SAVI.



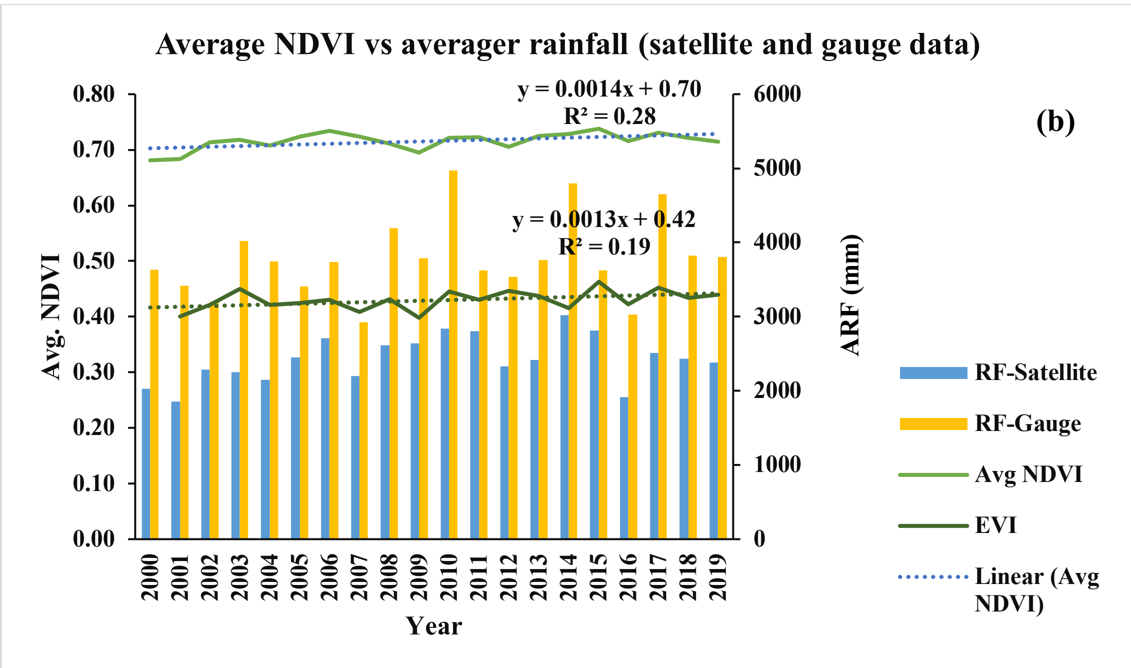


Figure 8. (a) Landsat-derived: NDVI, EVI and SAVI distribution over the period in the Central Highlands and (b) MODIS-derived: NDVI and EVI distribution over the period with annual average rainfall (ARF- satellite and gauge) in Ratnapura area (WL1a).

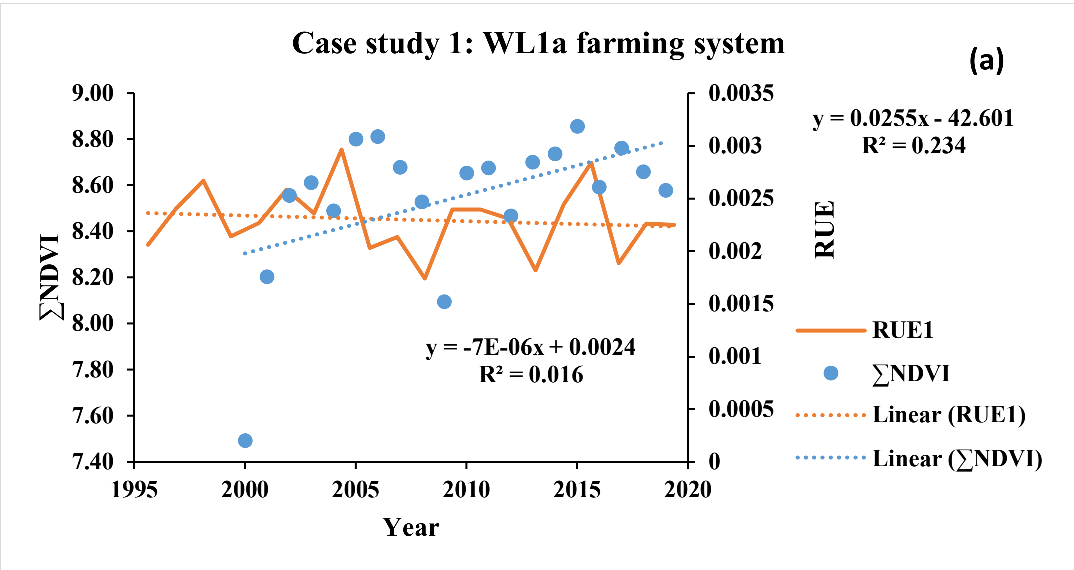
In this research, Landsat data provide the NDVI, EVI and SAVI values that demonstrate the combined effect of land-uses in the Central Highlands: dense forest, open forest, agriculture, water bodies and urban/built-up areas. For further analysis of crop diversity in farming systems, three case studies were conducted. From the analysis of three case studies, a similar pattern of NDVI, and EVI variation could be observed over the years (Appendix H, Figure H1-4). Further to this, the increasing trend of NDVI and EVI was greater than SAVI. Researchers also observed similar trends in other regions (Sarmah et al., 2018; Liu et al., 2018)**.** NDVI is closely related to the net and gross primary productivity. NDVI strongly correlates with plant biomass and net primary productivity (NPP), which is the difference between carbon fixed by photosynthesis and carbon lost to autotrophic respiration (Evans and Geerken, 2004). The MODIS-derived GPP and EVI provide reasonable estimates of productivity in the forest and grassland biomes (Waring et al., 2006). The MODIS derived NDVI and EVI values are positively correlated with NPP (0.76 and 0.53).

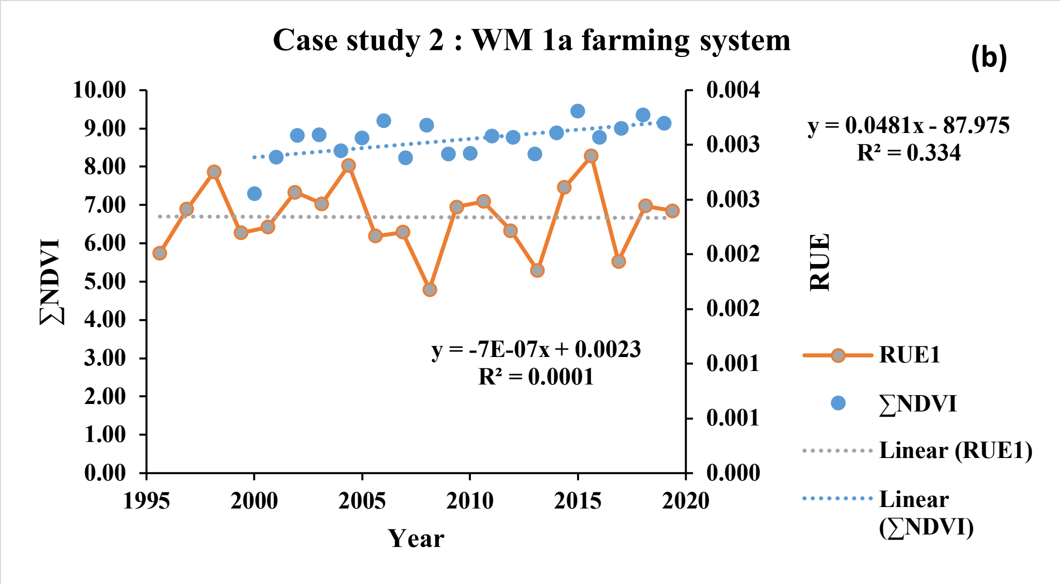
Earlier researchers have revealed a positive relationship between species richness and productivity (Fensholt et al., 2013), although the relationship may differ among ecosystems and dependent on spatial scales. Therefore, increasing trends in vegetation indices may indicate increasing heterogeneity or species diversity. Hence, this study further analyzed crop diversity and evenness using the Shannon diversity index derived from MODIS data. Nagendra (2002) described landscape diversity as evaluating richness and evenness in the context of measuring diversity. Richness refers to the number of different species (land cover types) in the landscape, and evenness refers to the relative percentage of land distributed amongst these different cover types. The Shannon diversity index of these three case studies shows some change over the period (Appendix J). However, the most prominent change was observed in the farming system of WL1a. The richness and evenness have decreased in WL1a from 2000 to 2019. The evenness values have changed on WM1a in this period. The reasons for these changes would be land fragmentation, land degradation, land-use change, and landslides during this period.

NDVI and EVI relationships between rainfalls were also observed. It is somewhat surprising to note a weak correlation between NDVI and rainfall ($r = 0.22$). However, there is a moderate positive correlation between EVI and rainfall ($r = 0.45$) (Appendix I, Table I1). The correlation between NDVI and EVI was observed as $r = 0.36$. Pau et al. (2012) indicated that precipitation and structural complexity strongly affected the correlation between the NDVI and plant species. Precipitation has a consistent direct effect on the NDVI and species richness. However, structural complexity has strong direct and indirect effects on the NDVI. The increase in rainfall would enhance the growth of weeds and crop growth in farming systems. These may be reasons for the increase in NDVI value in the study. The effect of rainfall can be normalized by employing rain use efficiency (RUE). Researchers previously highlighted that the RUE index identifies land degradation that is independent from rainfall (Wessels et al., 2008; Prince et al., 1998).

4.4.1 Soil erosion hazards and crop diversity change

This study estimated the ratio between vegetation indices (VI) and rainfall in the farming systems of the three case studies. The time series analysis was executed from 2000 to 2019 to normalize the VI for the influence of rainfall. This is known as rain-use efficiency (RUE). The ratio between RUE and rainfall can be found in Appendix K (Table K1). Figure 9 shows the VI and RUE variations for the three case studies.





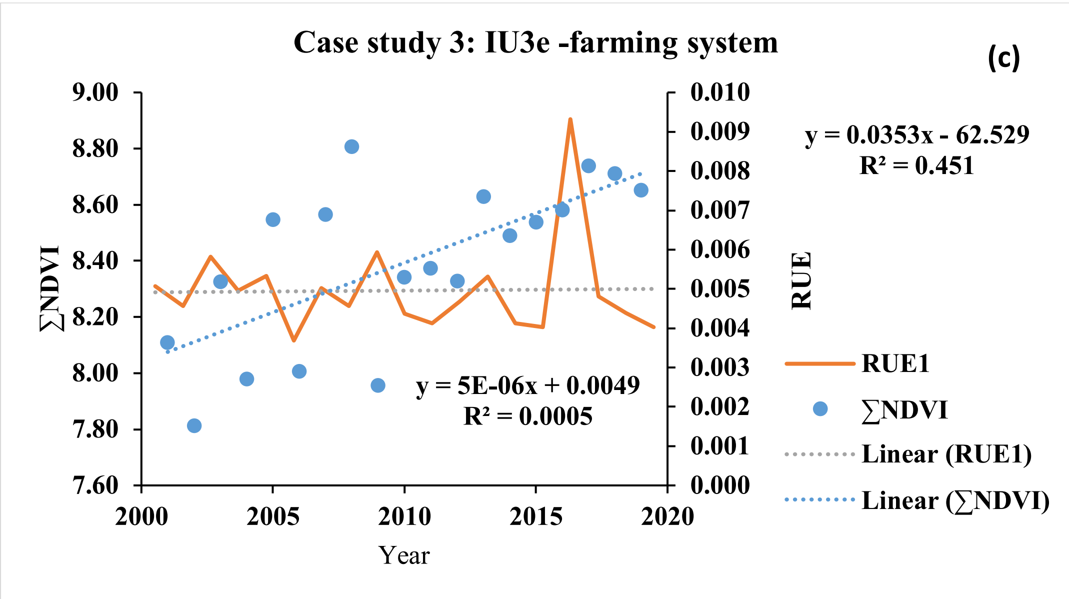


Figure 9. The trend of RUE in three farming systems: (a) WL1a, (b) WM1a, and (c) IU3e farming systems.

The farming systems WL1a and WM1a showed a negative trend of the RUE index, while IU3e showed a positive trend over the years. A similar trend of EVI based RUE (ΣEVI/rainfall) was also observed in farming systems WL1a and WM1a (see Appendix K, Table K2). The areas with a negative trend indicated land degradation. It is also noteworthy that these farming systems receive the highest rainfall compared to the IU3e. The positive trend of RUE in the IU3e farming system indicates the changes in increasing land cover or land conditions during the study period. The negative trend may occur due to land-use changes, which reduces NDVI values. Landmann and Dubovyk (2014) have observed a negative NDVI trend that indicates a gradual decline of vegetation cover or sudden land transformations such as deforestation.

This study examined the correlation between RUE and rainfall. There is a strong negative correlation between RUE and rainfall (r = -0.94, standard deviation = 0.001). Further to this, the coefficient of determination (R^2) was estimated to find the relationship between RUE, and rainfall. The results show there is a strong negative relationship between RUE and rainfall in three case studies: WL1a (R^2 =0.88), WM1a (R^2 =0.78), and IU3e (R^2 =0.86) (Appendix L, Figure L1).

The time-series analysis of MODIS VI was employed to obtain the RESTREND. The RESTREND of the three farming systems has shown a positive slope over the years. The farming system WL1a showed a slightly positive trend of RESTREND (R^2=0.23). However, the farming systems WM1a and IU3e reported a stronger positive trend of RESTREND R^2=0.33 and R^2=0.45, respectively. A similar trend of the EVI based RESTREND was also found in the same farming systems (Appendix K, Table K2). According to Kundu et al. (2017), the positive trend of RESTREND, indicates human interference on the landscape, such as plantation, cropping and agricultural development that supports increasing NDVI values. The findings of this study are also showing a positive trend of RESTREND. Hence, these findings provide evidence to prove the effect of human interference on the improvement of the vegetation cover in the three case studies. Farming system IU3e indicates the highest effect of human interference on the improvement of vegetation cover. Figure 10 shows the trends of RESTREND in the three case studies.

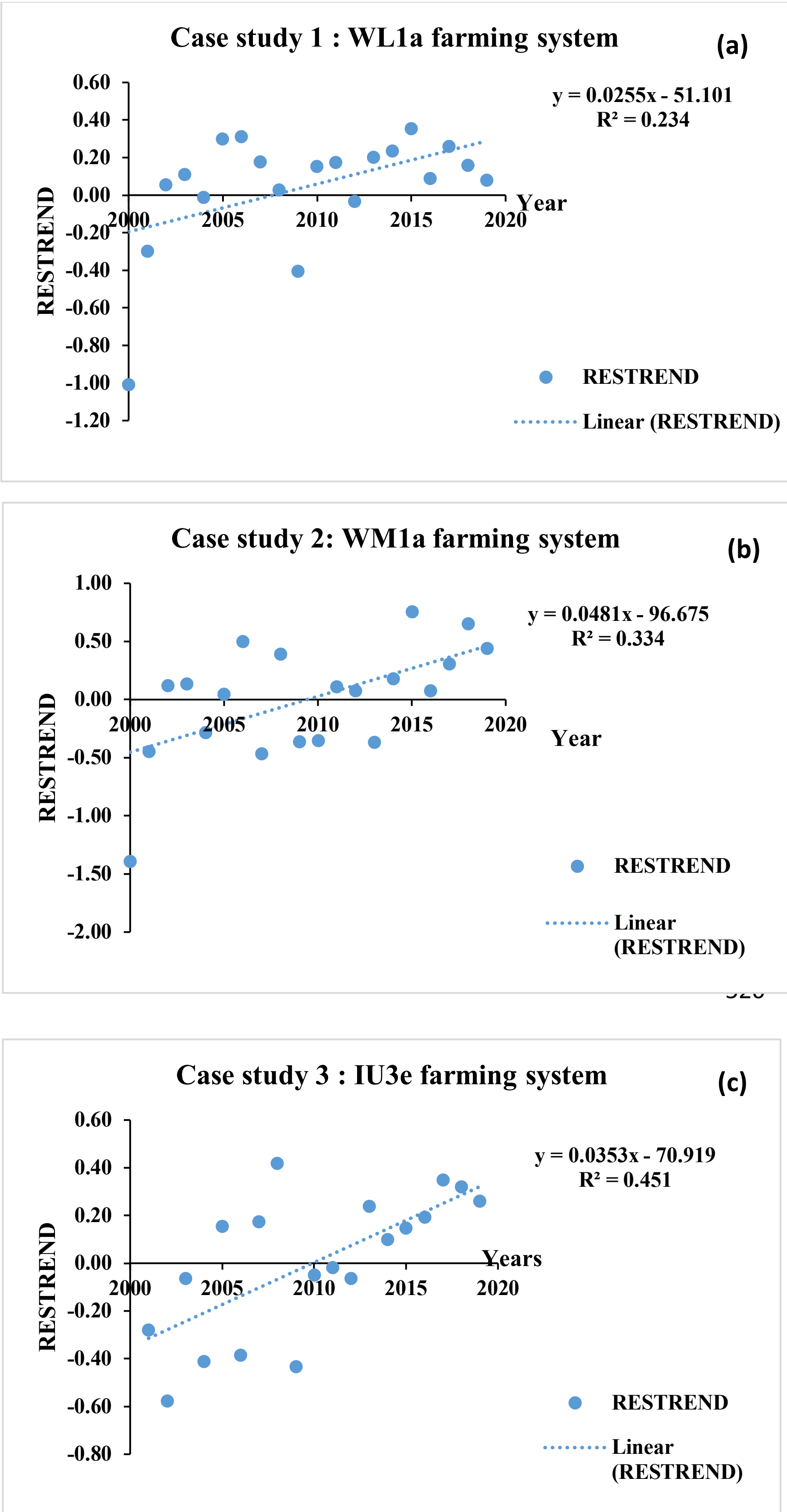


Figure 10. RESTREAND over the years: a) WM1a, b) WL1a, and c) IU3e farming systems.

4. Discussion

Spatial modeling with four assessments: LULC change, soil erosion hazards, rainfall variation, and crop diversity change assessments were conducted to address the research questions of the study. The LULC evaluation indicates forest and open forest areas have decreased while agricultural and built-up areas have increased during the study period. Other studies also indicated similar findings in their researches (Jayawardena et al., 2018). This study highlighted the large-scale deforestation, which has taken place due to agricultural activities, expansion of home gardens and construction of household settlements. According to a recent study, forest area is decreasing in Sri Lanka (Mondal et al., 2020). Ranasinghe et al. (2019) also confirmed some of these findings, such as decreasing the forest cover and increasing home gardens and agricultural areas in Bandula district of the Central Highlands during the period of 1990 to 2018. These findings clearly show the anthropogenic impact on natural ecosystems during the past few decades.

According to the RUSLE analysis, the majority of the land area of the Central Highlands, in an ecological and economic sense, has been subjected to soil erosion over the past two decades. The analysis revealed high and very-high soil erosion classes, representing 18.04% of the total land area. The global investigation of modeling and mapping studies (GIMMS) in 1981–2003 has indicated 32.09% of the land area was under degradation in Sri Lanka (Bai et al., 2012). The higher rate of soil erosion was evident from the amount of silt piling up behind the dams across the Mahaweli River, which drains through the greater part of the Central Highlands (Khaniya et al., 2019).

In addition, the rainfall variation in terms of the increase of rainfall intensity and average rainfall was observed during this study period. A significant increase in rainfall intensity could be observed in Nuwara Eliya. This study found a positive correlation between average annual rainfall and soil erosion. Ratnayake and Herath (2005) claimed spatial locations of recent landslides in the Central Highlands correlate highly with an increase in rainfall intensity. A recent study further revealed a recent incidence of a landslide in the Aranayake area in the Central Highlands, which was triggered by heavy, intense rainfall. This soil mass movement caused great damage in the Aranayake area by killing 127 people and demolishing 75 houses (Dang et al., 2019). However, the impact of climatic variation, particularly rainfall variation in the Central Highlands, is not uniform everywhere.

The drastic land-use changes may cause changes in heat and moisture fluxes that would lead to local rainfall variation. In addition, the relationship between rainfall and temperature may be a result of factors such as global warming and land-use change. The increase in sea surface temperature may also be responsible for the increase in rainfall in the western part of the Central Highlands (Wickramagamage, 1998). Scholars indicated the moisture retention capacity of the atmosphere might increase by 7% by increasing global mean temperature from one degree Celsius (Mullan et al., 2012; Almagro et al., 2017). The increasing atmospheric water vapor may change the hydrological cycle and induce more intensive precipitation events (Nearing et al., 2005; Mullan et al., 2012).

Studies show that the onset of the two-monsoon pattern (southwest and northeast) in Sri Lanka has also been altered, and the increase of rainfall intensity could be observed in the recent past (Jayawardena et al., 2018; Burt and Weerasinghe, 2014). The changes of onset of monsoons have been affected farming activities in the Central Highlands. The smallholdings and rain-fed agriculture dominate the Central Highlands. Borrelli et al. (2017) also highlighted that the most severe impacts of global climate change would be felt mostly on smallholder farmers in developing countries.

The NDVI, EVI and standard deviations of GPP across the highlands were used as measures of vegetation heterogeneity. Ecosystem productivity has shown a good correlation with species diversity, as it is the integrative expression of factors such as topography, land use, disturbance, and soil nutrients (Evans and Geerken, 2004; John et al., 2008). As a measure of plant diversity, plant species richness is often considered a measure of ecosystem health and resilience (Symstad and Jonas, 2011). Pohl et al. (2009) indicated that plant species richness significantly increased the topsoil aggregate stability on slopes.

In the crop diversity assessment of this study, NDVI was normalized by rainfall (RUE index). Findings show a decreasing trend of RUE in WL1a and WM1a farming systems. Further to this, soil erosion of these two farming systems is also high. Previous research emphasizes that a decreasing trend of RUE indicates land degradation that is independent from rainfall (Wessels et al., 2008; Prince et al., 1998). Thus, the findings of this study confirmed the land degradation in WL1a and WM1a farming systems. Levin et al. (2007) found that a decreasing trend of vegetation indices would be an indication of the decreasing heterogeneity or species diversity. The Shannon index (plant richness and evenness) in the WL1a and WM1a farming systems (western part of the Central Highlands) also decreases. Hence, the present study provides evidence for the decreasing of crop diversity. Besides, crop diversity in farmland can vary due to various reasons, such as socio-economic factors. Farmers would shift from one crop to another crop due to changes in market prices (Maitima et al., 2009), environmental influences or socio-economic factors in farming systems (Shrestha et al., 2010). Therefore, further assessment and ground-based validation are needed to generalize the correlation between soil erosion and plant diversity change.

The study further investigated land degradation using RESTREND analysis to distinguish human-induced land degradation. To interpret the NDVI trends in terms of land degradation or improvement, researchers have to eliminate the impact of climatic variability from the residual sum of NDVI to detect human influence (Wessels et al., 2007; Kundu et al., 2017). A negative trend of RESTREND indicates human-induced land degradation, while a positive trend of RESTREND indicates human influences on the improvement of vegetation (Kundu et al.,2017; Evans, 2004). The present study demonstrates an increasing trend of RESTREND, which means an improvement of vegetation cover in the farming systems. Findings provide evidence to prove the effect of human interference on the improvement of vegetation in three case studies.

The increasing farming areas, improved farming techniques, and land reclamation may be the reasons for improving vegetation cover. Similarly, Burrell et al. (2017) found that certain farming practices such as fertilizer applications, irrigation, high breed varieties of seasonal crops, etc. significantly increase the NDVI values. Fensholt et al. (2013) described trends of vegetation productivity as dependent on climatic factors and non-climatic factors such as land management, cropping practices, and nutrient status. Climatic factors are precipitation, atmospheric temperature, global sea surface temperature, and soil moisture (Fensholt et al., 2013; Ibrahim et al., 2015). Burrell et al. (2017) and other researchers argued that increasing trends of vegetation cover due to the long-term increasing trend of rainfall or CO_2 fertilization due to anthropogenic greenhouse gas emissions (Sarmah et al., 2018; Anyamba and Tucker, 2005).

There are several important areas in this study that make an original contribution to the body of knowledge; extraction of farming systems based on the agro-ecological regions, application of rain use efficiency and trend analysis for land degradation in farming systems, and residual trend analysis to distinguish the human-induced land degradation at a farming system level. To the best of the knowledge of the authors of this paper, no studies have previously been conducted to integrate these aspects at a farming system level in Sri Lanka. The present study gives a novel spatial modeling approach by combining LULC, soil erosion hazards, crop diversity change, and rainfall variation. Moreover, this study provides comprehensive scientific insights into sustainable land and farming system management. These insights are very critical in developing strategies to ensure food security and sustainable land management (Visser et al., 2019; Djekic et al., 2021). In other words, food security and sustainable land management are paramount two aspects in achieving sustainable development goals (SGDs) and 2030 agenda: particularly in achieving goals 2 and 15 (Zero hunger and Life on land). Hence, this research contributes to developing strategies in achieving SGDs of the United Nations. However, there are some limitations to this study. The relationship between rainfall and plant water availability is not a simple process, and only a fraction of the rainfall, becomes available for transpiration and evaporation. These parameters did not consider in this study. In addition, an increase in temperature and CO_2 changes were also not considered.

The model developed by this study can be used for early detection and to reduce the potential adverse impact of climate change and future damages to farming systems. Hence, this approach provides a basis for a new direction for future research. The policy implication of this study provides a direction towards developing strategies for land management and resilience building, guiding future land-use planning for the soil and ecological conservation in areas under high and very high soil erosion categories to protect the farming systems sustainably. The significance of this study implies an improved understanding of soil erosion hazards caused by rainfall variation and crop diversity changes through remote sensing applications, accompanied to formulate climate risk management strategies and mitigation measures for better management of farming systems and risk reduction.

5. Conclusion

This paper presents time-series segmentation of LULC change, soil erosion hazards, crop diversity change, and rainfall variation in the Central Highlands of Sri Lanka from 2000 to 2019. The LULC indicates agricultural lands (15.4%) and built-up areas (2.35%) have been increasing while reducing the dense forest(14.5%) and open forest cover(5.8%). The soil erosion has increased from 9.08 Mg/ha/yr to 11.08 Mg/ha/yr. The rainfall variation revealed a significantly increasing trend. Crop diversity has also been decreased in the WL1a (SHDI from o.45 to 0.41) and WM1a (SHDI from 0.69 to 0.65) farming systems. Furthermore, a positive trend of RESTREND is reported in WL1a ,WM1a and IU3e farming systems. This is evidence to prove the effect of human interference on the improvement of vegetation in the WL1a, WM1a and IU3e farming systems. It suggests climate-induced soil erosion may be responsible for land degradation in these farming systems. These findings imply the complex relationships among soil erosion, plant diversity change and rainfall variation. The combined spatial modeling approach provides a better understanding of the ground situation and can predict the situation with a meaningful outcome. Remote sensing derived NDVI and EVI indices provide the best solution for monitoring vegetation cover and plant diversity change. Overall, these findings are evidence that human-induced LULC change and climate-induced land degradation create significant damage to farming systems that greatly threaten the food production of the Central Highlands of Sri Lanka.

Funding: The research is supported by the Centre for Advanced Modeling and Geospatial Information Systems (CAMGIS), Faculty of Engineering & IT, University of Technology Sydney.

Author Contributions: Conceptualization, S.S. and B.P.; methodology, S.S., B.P.; software, S.S., BP., A.H.; validation, S.S.; formal analysis, S.S.; writing—original draft preparation, S.S.; writing—review and editing, S.S., B.P., A.H. and J.B..; supervision, B.P., A.H. and J.B.; funding acquisition, B.P.

Declaration of Competing Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Reference

Alewell, C., Borrelli, P., Meusburger, K., Panagos, P., 2019. Using the USLE: Chances, challenges and limitations of soil erosion modelling. Int. Soil Water Conserv. Res. https://doi.org/10.1016/j.iswcr.2019.05.004

Almagro, A., Oliveira, P.T.S., Nearing, M.A., Hagemann, S., 2017. Projected climate change impacts in rainfall erosivity over Brazil. Sci. Rep. 7, 1–12. https://doi.org/10.1038/s41598-017-08298-y

Angima, S.D., Stott, D.E., O’Neill, M.K., Ong, C.K., Weesies, G.A., 2003. Soil erosion prediction using RUSLE for central Kenyan highland conditions. Agric. Ecosyst. Environ. 97, 295–308. https://doi.org/10.1016/S0167-8809(03)00011-2

Anyamba, A., Tucker, C.J., 2005. Analysis of Sahelian vegetation dynamics using NOAA-AVHRR NDVI data from 1981-2003, in: Journal of Arid Environments. Academic Press, pp. 596–614. https://doi.org/10.1016/j.jaridenv.2005.03.007

Auerswald, K., Menzel, A., 2021. Change in erosion potential of crops due to climate change. Agric. For. Meteorol. 300, 108338. https://doi.org/10.1016/j.agrformet.2021.108338

Baez-Villanueva, O.M., Zambrano-Bigiarini, M., Ribbe, L., Nauditt, A., Giraldo-Osorio, J.D., Thinh, N.X., 2018. Temporal and spatial evaluation of satellite rainfall estimates over different regions in Latin-America. Atmos. Res. 213, 34–50. https://doi.org/10.1016/j.atmosres.2018.05.011

Bai, Z.G., Conijn, J.G., Bindraban, P.S., Rutgers, B., 2012. Global changes of remotely sensed greenness and simulated biomass production since 1981: towards mapping global soil degradation. Rep. - ISRIC World Soil Inf. 33 pp.

Berendse, F., van Ruijven, J., Jongejans, E., Keesstra, S., 2015. Loss of plant species diversity reduces soil erosion resistance. Ecosystems 18, 881–888. https://doi.org/10.1007/s10021-015-9869-6

Bishop, Y.M., Holland, P.W., Fienberg, S.E., 2007. Discrete multivariate analysis theory and practice, Discrete Multivariate Analysis Theory and Practice. Springer New York. https://doi.org/10.1007/978-0-387-72806-3

Borrelli, P., Panagos, P., 2020. An indicator to reflect the mitigating effect of Common Agricultural Policy on soil erosion. Land use policy 92, 104467. https://doi.org/10.1016/j.landusepol.2020.104467

Borrelli, P., Robinson, D.A., Fleischer, L.R., Lugato, E., Ballabio, C., Alewell, C., Meusburger, K., Modugno, S., Schütt, B., Ferro, V., Bagarello, V., Oost, K. Van, Montanarella, L., Panagos, P., 2017. An assessment of the global impact of 21st century land use change on soil erosion. Nat. Commun. 8, 2017. https://doi.org/10.1038/s41467-017-02142-7

Burrell, A.L., Evans, J.P., Liu, Y., 2017. Detecting dryland degradation using Time Series Segmentation and Residual Trend analysis (TSS-RESTREND). Remote Sens. Environ. 197, 43–57. https://doi.org/10.1016/j.rse.2017.05.018

Burt, T.P., Weerasinghe, K.D.N., 2014. Rainfall distributions in Sri Lanka in time and space: An analysis based on daily rainfall data. Climate 2, 242–263. https://doi.org/10.3390/cli2040242

Chander, G., Markham, B.L., Helder, D.L., 2009. Summary of current radiometric calibration coefficients for Landsat MSS, TM, ETM+, and EO-1 ALI sensors. Remote Sens. Environ. 113, 893–903. https://doi.org/10.1016/j.rse.2009.01.007

Chavez, P.S., 1996. Image-based atmospheric corrections - Revisited and improved. Photogramm. Eng. Remote Sensing 62, 1025–1036.

Chitale, V.S., Behera, M.D., Roy, P.S., 2019. Deciphering plant richness using satellite remote sensing: a study from three biodiversity hotspots. Biodivers. Conserv. 28, 2183–2196. https://doi.org/10.1007/s10531-019-01761-4

Cortes, C., Vapnik, V., 1995. Support-vector networks. Mach. Learn. 20, 273–297. https://doi.org/10.1007/bf00994018

Cunha, J., Nóbrega, R.L.B., Rufino, I., Erasmi, S., Galvão, C., Valente, F., 2020. Surface albedo as a proxy for land-cover clearing in seasonally dry forests: Evidence from the Brazilian Caatinga. Remote Sens. Environ. 238, 111250. https://doi.org/10.1016/j.rse.2019.111250

Dang, K., Sassa, K., Konagai, K., Karunawardena, A., Bandara, R.M.S., Hirota, K., Tan, Q., Ha, N.D., 2019. Recent rainfall-induced rapid and long-traveling landslide on 17 May 2016 in Aranayaka, Kagelle District, Sri Lanka. Landslides 16, 155–164. https://doi.org/10.1007/s10346-018-1089-7

Djekic, I., Batlle-Bayer, L., Bala, A., Fullana-I-palmer, P., Jambrak, A.R., 2021. Role of the food supply chain stakeholders in achieving un sdgs. Sustain. 13. https://doi.org/10.3390/su13169095

Eckstein, D., Winges, M., Marie-Lena, H., 2019. Global climate risk index 2019 [WWW Document]. URL https://germanwatch.org/en/16046 (accessed 5.8.21).

Esham, M., Garforth, C., 2013. Climate change and agricultural adaptation in Sri Lanka: A review. Clim. Dev. https://doi.org/10.1080/17565529.2012.762333

Evans, J., Geerken, R., 2004. Discrimination between climate and human-induced dryland degradation. J. Arid Environ. 57, 535–554. https://doi.org/10.1016/S0140-1963(03)00121-6

Fensholt, R., Rasmussen, K., Kaspersen, P., Huber, S., Horion, S., Swinnen, E., 2013. Assessing land degradation/recovery in the african sahel from long-term earth observation based primary productivity and precipitation relationships. Remote Sens. 5, 664–686. https://doi.org/10.3390/rs5020664

Fenta, A.A., Tsunekawa, A., Haregeweyn, N., Tsubo, M., Yasuda, H., Kawai, T., Ebabu, K., Berihun, M.L., Belay, A.S., Sultan, D., 2021. Agroecology-based soil erosion assessment for better conservation planning in Ethiopian river basins. Environ. Res. 195, 110786. https://doi.org/10.1016/j.envres.2021.110786

Fernández, C., Vega, J.A., 2018. Evaluation of the rusle and disturbed wepp erosion models for predicting soil loss in the first year after wildfire in NW Spain. Environ. Res. 165, 279–285. https://doi.org/10.1016/j.envres.2018.04.008

Ganasri, B.P., Ramesh, H., 2016. Assessment of soil erosion by RUSLE model using remote sensing and GIS - A case study of Nethravathi Basin. Geosci. Front. 7, 953–961. https://doi.org/10.1016/j.gsf.2015.10.007

Gupta, H. V., Kling, H., Yilmaz, K.K., Martinez, G.F., 2009. Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling. J. Hydrol. 377, 80–91. https://doi.org/10.1016/j.jhydrol.2009.08.003

Han, J., Ge, W., Hei, Z., Cong, C., Ma, C., Xie, M., Liu, B., Feng, W., Wang, F., Jiao, J., 2020. Agricultural land use and management weaken the soil erosion induced by extreme rainstorms. Agric. Ecosyst. Environ. 301, 107047. https://doi.org/10.1016/j.agee.2020.107047

Hewawasam, T., 2010. Effect of land use in the upper Mahaweli catchment area on erosion landslides and siltation in hydropower reservoirs of Sri Lanka. J. Natl. Sci. Found. Sri Lanka 38, 3–14. https://doi.org/10.4038/jnsfsr.v38i1.1721

Hewawasam, T., Illangasinghe, S., 2015. Quantifying sheet erosion in agricultural highlands of Sri Lanka by tracking grain-size distributions. Anthropocene 11, 25–34. https://doi.org/10.1016/j.ancene.2015.11.004

Hewawasam, T., von Blanckenburg, F., Bouchez, J., Dixon, J.L., Schuessler, J.A., Maekeler, R., 2013. Slow advance of the weathering front during deep, supply-limited saprolite formation in the tropical Highlands of Sri Lanka. Geochim. Cosmochim. Acta 118, 202–230. https://doi.org/10.1016/j.gca.2013.05.006

Hou, J., Wang, H., Fu, B., Zhu, L., Wang, Y., Li, Z., 2016. Effects of plant diversity on soil erosion for different vegetation patterns. Catena 147, 632–637. https://doi.org/10.1016/j.catena.2016.08.019

Huete, A., Didan, K., Miura, T., Rodriguez, E.P., Gao, X., Ferreira, L.G., 2002. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sens. Environ. 83, 195–213. https://doi.org/10.1016/S0034-4257(02)00096-2

Huete, A.R., 1988. A soil-adjusted vegetation index (SAVI). Remote Sens. Environ. 25, 295–309. https://doi.org/10.1016/0034-4257(88)90106-X

Hunt, N.D., Hill, J.D., Liebman, M., 2019. Cropping System Diversity Effects on Nutrient Discharge, Soil Erosion, and Agronomic Performance. Environ. Sci. Technol. 53, 1344–1352. https://doi.org/10.1021/acs.est.8b02193

Ibrahim, Y.Z., Balzter, H., Kaduk, J., Tucker, C.J., 2015. Land degradation assessment using residual trend analysis of GIMMS NDVI3g, soil moisture and rainfall in Sub-Saharan West Africa from 1982 to 2012. Remote Sens. 7, 5471–5494.

https://doi.org/10.3390/rs70505471

Jayawardena, I.M.S.P., Darshika, D.W.T.T., C. Herath, H.M.R., 2018. Recent Trends in Climate Extreme Indices over Sri Lanka. Am. J. Clim. Chang. 07, 586–599. https://doi.org/10.4236/ajcc.2018.74036

John, R., Chen, J., Lu, N., Guo, K., Liang, C., Wei, Y., Noormets, A., Ma, K., Han, X., 2008. Predicting plant diversity based on remote sensing products in the semi-arid region of Inner Mongolia. Remote Sens. Environ. 112, 2018–2032. https://doi.org/10.1016/j.rse.2007.09.013

Khaniya, B., Jayanayaka, I., Jayasanka, P., Rathnayake, U., 2019. Rainfall Trend Analysis in Uma Oya Basin, Sri Lanka, and Future Water Scarcity Problems in Perspective of Climate Variability. Adv. Meteorol. 2019. https://doi.org/10.1155/2019/3636158

Kling, J.R., Mullainathan, S., Shafir, E., Vermeulen, L.C., Wrobel, M. V., 2012. Comparison friction: Experimental evidence from medicare drug plans. Q. J. Econ. 127, 199–235. https://doi.org/10.1093/qje/qjr055

Kundu, A., Patel, N.R., Saha, S.K., Dutta, D., 2017. Desertification in western Rajasthan (India): an assessment using remote sensing derived rain-use efficiency and residual trend methods. Nat. Hazards 86, 297–313. https://doi.org/10.1007/s11069-016-2689-y

Lal, R., 2011. Climate of South Asia and the Human Wellbeing, in: Climate Change and Food Security in South Asia. Springer Netherlands, pp. 3–12. https://doi.org/10.1007/978-90-481-9516-9_1

Landmann, T., Dubovyk, O., 2014. Spatial analysis of human-induced vegetation productivity decline over eastern Africa using a decade (2001-2011) of medium resolution MODIS time-series data. Int. J. Appl. Earth Obs. Geoinf. 33, 76–82. https://doi.org/10.1016/j.jag.2014.04.020

Lee, S., Talib, J.A., 2005. Probabilistic landslide susceptibility and factor effect analysis. Environ. Geol. 47, 982–990. https://doi.org/10.1007/s00254-005-1228-z

Levin, N., Shmida, A., Levanoni, O., Tamari, H., Kark, S., 2007. Predicting mountain plant richness and rarity from space using satellite-derived vegetation indices. Divers. Distrib. 13, 692–703. https://doi.org/10.1111/j.1472-4642.2007.00372.x

Liu, H.Q., Huete, A., 1996. A feedback based modification of the NDVI to minimize canopy background and atmospheric noise. IEEE Trans. Geosci. Remote Sens. 33, 457–465. https://doi.org/10.1109/tgrs.1995.8746027

Liu, J., Gao, G., Wang, S., Jiao, L., Wu, X., Fu, B., 2018. The effects of vegetation on runoff and soil loss: Multidimensional structure analysis and scale characteristics. J. Geogr. Sci.

28, 59–78. https://doi.org/10.1007/s11442-018-1459-z

Liu, Y., Li, Y., Li, S., Motesharrei, S., 2015. Spatial and temporal patterns of global NDVI trends: Correlations with climate and human factors. Remote Sens. 7, 13233–13250. https://doi.org/10.3390/rs71013233

LPDAAC, 2021. Land Processes Distributed Active Archive Center [WWW Document]. NASA EOSDIS L. Process. DAAC, USGS Earth Resour. Obs. Sci. Center, Sioux Falls, South Dakota. URL https://lpdaac.usgs.gov/ (accessed 6.20.21).

Maitima, J.M., Mugatha, S.M., Reid, R.S., Gachimbi, L.N., Majule, A., Lyaruu, H., Pomery, D., Mathai, S., Mugisha, S., 2009. The linkages between land use change, land degradation and biodiversity across East Africa. African J. Environ. Sci. Technol. 3, 310–325. https://doi.org/10.5897/AJEST08.173

McLeod, A., McLeod, M., 2014. Package "Kendall," cran.microsoft.com.

Meena, S.R., Ghorbanzadeh, O., Blaschke, T., 2019. A comparative study of statistics-based landslide susceptibility models: A case study of the region affected by the Gorkha earthquake in Nepal. ISPRS Int. J. Geo-Information 8. https://doi.org/10.3390/ijgi8020094

Mondal, P., McDermid, S.S., Qadir, A., 2020. A reporting framework for Sustainable Development Goal 15: Multi-scale monitoring of forest degradation using MODIS, Landsat and Sentinel data. Remote Sens. Environ. 237. https://doi.org/10.1016/j.rse.2019.111592

Morisette, J.T., Jarnevich, C.S., Ullah, A., Cai, W., Pedelty, J.A., Gentle, J.E., Stohlgren, T.J., Schnase, J.L., 2006. A tamarisk habitat suitability map for the continental United States. Front. Ecol. Environ. 4, 11–17. https://doi.org/10.1890/1540-9295(2006)004[0012:ATHSMF]2.0.CO;2

Mullan, D., Favis-Mortlock, D., Fealy, R., 2012. Addressing key limitations associated with modelling soil erosion under the impacts of future climate change. Agric. For. Meteorol. 156, 18–30. https://doi.org/10.1016/j.agrformet.2011.12.004

Nagendra, H., 2002. Opposite trends in response for the Shannon and Simpson indices of landscape diversity. Appl. Geogr. 22, 175–186. https://doi.org/10.1016/S0143-6228(02)00002-4

Nagendra, H., Rocchini, D., Ghate, R., Sharma, B., Pareeth, S., 2010. Assessing plant diversity in a dry tropical forest: Comparing the utility of landsat and ikonos satellite images. Remote Sens. 2, 478–496. https://doi.org/10.3390/rs2020478

Nampak, H., Pradhan, B., Mojaddadi Rizeei, H., Park, H.J., 2018. Assessment of land cover and land use change impact on soil loss in a tropical catchment by using multitemporal SPOT-5 satellite images and Revised Universal Soil Loss Equation model. L. Degrad. Dev. 29, 3440–3455. https://doi.org/10.1002/ldr.3112

Nay, J., Burchfield, E., Gilligan, J., 2018. A machine-learning approach to forecasting remotely sensed vegetation health. Int. J. Remote Sens. 39, 1800–1816. https://doi.org/10.1080/01431161.2017.1410296

Nearing, M.A., Jetten, V., Baffaut, C., Cerdan, O., Couturier, A., Hernandez, M., Le Bissonnais, Y., Nichols, M.H., Nunes, J.P., Renschler, C.S., Souchère, V., Van Oost, K., 2005. Modeling response of soil erosion and runoff to changes in precipitation and cover, in: Catena. Elsevier, pp. 131–154. https://doi.org/10.1016/j.catena.2005.03.007

Olofsson, P., Foody, G.M., Stehman, S. V., Woodcock, C.E., 2013. Making better use of accuracy data in land change studies: Estimating accuracy and area and quantifying uncertainty using stratified estimation. Remote Sens. Environ. 129, 122–131. https://doi.org/10.1016/j.rse.2012.10.031

ORNL DAAC, 2018. MODIS and VIIRS Land Products Global Subsetting and Visualization Tool [WWW Document]. ORNL DAAC, Oak Ridge, Tennessee, USA. URL https://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=1379 (accessed 6.25.21).

Panagos, P., Katsoyiannis, A., 2019. Soil erosion modelling: The new challenges as the result of policy developments in Europe. Environ. Res. https://doi.org/10.1016/j.envres.2019.02.043

Pau, S., Gillespie, T.W., Wolkovich, E.M., 2012. Dissecting NDVI-species richness relationships in Hawaiian dry forests. J. Biogeogr. 39, 1678–1686. https://doi.org/10.1111/j.1365-2699.2012.02731.x

Pohl, M., Alig, D., Körner, C., Rixen, C., 2009. Higher plant diversity enhances soil stability in disturbed alpine ecosystems. Plant Soil 324, 91–102. https://doi.org/10.1007/s11104-009-9906-3

Pouteau, R., Gillespie, T.W., Birnbaum, P., 2018. Predicting tropical tree species richness from normalized difference vegetation index time series: The devil is perhaps not in the detail. Remote Sens. 10, 698. https://doi.org/10.3390/rs10050698

Pradhan, B., Chaudhari, A., Adinarayana, J., Buchroithner, M.F., 2012. Soil erosion assessment and its correlation with landslide events using remote sensing data and GIS: A case study at Penang Island, Malaysia. Environ. Monit. Assess. 184, 715–727. https://doi.org/10.1007/s10661-011-1996-8

Prince, S.D., Colstoun, E.B.D., Kravitz, L.L., 1998. Evidence from rain-use efficiencies does not indicate extensive Sahelian desertification. Glob. Chang. Biol. 4, 359–374. https://doi.org/10.1046/j.1365-2486.1998.00158.x

Qi, Z., Yeh, A.G.O., Li, X., Lin, Z., 2012. A novel algorithm for land use and land cover classification using RADARSAT-2 polarimetric SAR data. Remote Sens. Environ. 118, 21–39. https://doi.org/10.1016/j.rse.2011.11.001

Ranasinghe, A.K.R.N., Bandara, R., Puswewala, U.G.A., Dammalage, T.L., 2019. Efficacy of using Radar Induced Factors in Landslide Susceptibility Analysis: case study of Koslanda, Sri Lanka. Nat. Hazards Earth Syst. Sci. Discuss. 1–22. https://doi.org/10.5194/nhess-2018-335

Rathnayake, C.W., Jones, S., Soto-Berelov, M., 2020. Mapping land cover change over a 25-year period (1993-2018) in Sri Lanka using landsat time-series. Land 9, 27. https://doi.org/10.3390/land9010027

Ratna, S.B., Cherchi, A., Osborn, T.J., Joshi, M., Uppara, U., 2021. The Extreme Positive Indian Ocean Dipole of 2019 and Associated Indian SummerRatna, Satyaban B., Annalisa Cherchi, Timothy J. Osborn, Manoj Joshi, and Umakanth Uppara. 2021. “The Extreme Positive Indian Ocean Dipole of 2019 and Associated Indian Summer Mo. Geophys. Res. Lett. https://doi.org/10.1029/2020GL091497

Ratnayake, U., Herath, S., 2005. Changing rainfall and its impact on landslides in Sri Lanka. J. Mt. Sci. 2, 218–224. https://doi.org/10.1007/bf02973195

Rizeei, H.M., Saharkhiz, M.A., Pradhan, B., Ahmad, N., 2016. Soil erosion prediction based on land cover dynamics at the Semenyih watershed in Malaysia using LTM and USLE models. Geocarto Int. 31, 1158–1177. https://doi.org/10.1080/10106049.2015.1120354

Rouse, J.W., Haas, R.H., Schell, J.A., Deering, D.W., 1974. Monitoring Vegetation Systems in the Great Plains with Erts, in: Stanley C. Freden, Enrico P. Mercanti, and M.A.B. (Ed.), Third Earth Resources Technology Satellite-1 Symposium- Volume I: Technical Presentations. NASA SP. published by NASA, Washington, D.C., Washington, D.C., USA, p. 309.

Rozos, D., Skilodimou, H.D., Loupasakis, C., Bathrellos, G.D., 2013. Application of the revised universal soil loss equation model on landslide prevention. An example from N. Euboea (Evia) Island, Greece. Environ. Earth Sci. 70, 3255–3266. https://doi.org/10.1007/s12665-013-2390-3

Sadeghi, M., Nguyen, P., Naeini, M.R., Hsu, K., Braithwaite, D., Sorooshian, S., 2021. PERSIANN-CCS-CDR, a 3-hourly 0.04° global precipitation climate data record for heavy precipitation studies. Sci. Data 8. https://doi.org/10.1038/s41597-021-00940-9

Sarmah, S., Jia, G., Zhang, A., 2018. Satellite view of seasonal greenness trends and controls in South Asia. Environ. Res. Lett. 13. https://doi.org/10.1088/1748-9326/aaa866

Şen, Z., 2012. Innovative Trend Analysis Methodology. J. Hydrol. Eng. 17, 1042–1046. https://doi.org/10.1061/(asce)he.1943-5584.0000556

Senanayake, S., Pradhan, B., Huete, A., Brennan, J., 2021. Proposing an ecologically viable and economically sound farming system using a matrix-based geo-informatics approach. Sci. Total Environ. 794, 148788. https://doi.org/10.1016/j.scitotenv.2021.148788

Senanayake, S., Pradhan, B., Huete, A., Brennan, J., 2020a. A Review on Assessing and Mapping Soil Erosion Hazard Using Geo-Informatics Technology for Farming System Management. Remote Sens. 12, 4063. https://doi.org/10.3390/rs12244063

Senanayake, S., Pradhan, B., Huete, A., Brennan, J., 2020b. Assessing Soil Erosion Hazards Using Land-Use Change and Landslide Frequency Ratio Method: A Case Study of Sabaragamuwa Province, Sri Lanka. Remote Sens. 12, 1483. https://doi.org/10.3390/rs12091483

Shannon, C.E., 1948. A Mathematical Theory of Communication. Bell Syst. Tech. J. 27, 379–423. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x

Shrestha, R.P., Schmidt-Vogt, D., Gnanavelrajah, N., 2010. Relating plant diversity to biomass and soil erosion in a cultivated landscape of the eastern seaboard region of Thailand. Appl. Geogr. 30, 606–617. https://doi.org/10.1016/j.apgeog.2010.01.005

Singh, S.K., Srivastava, P.K., Gupta, M., Thakur, J.K., Mukherjee, S., 2014. Appraisal of land use/land cover of mangrove forest ecosystem using support vector machine. Environ. Earth Sci. 71, 2245–2255. https://doi.org/10.1007/s12665-013-2628-0

Sivakumar, M.V.K., 2007. Interactions between climate and desertification. Agric. For. Meteorol. 142, 143–155. https://doi.org/10.1016/j.agrformet.2006.03.025

Sun, Q., Miao, C., Duan, Q., Ashouri, H., Sorooshian, S., Hsu, K.L., 2018. A Review of Global Precipitation Data Sets: Data Sources, Estimation, and Intercomparisons. Rev. Geophys. 56, 79–107. https://doi.org/10.1002/2017RG000574

Symstad, A.J., Jonas, J.L., 2011. Incorporating biodiversity into rangeland health: Plant species richness and diversity in great plains grasslands. Rangel. Ecol. Manag. 64, 555–572. https://doi.org/10.2111/REM-D-10-00136.1

Turner, W., Spector, S., Gardiner, N., Fladeland, M., Sterling, E., Steininger, M., 2003. Remote sensing for biodiversity science and conservation. Trends Ecol. Evol. https://doi.org/10.1016/S0169-5347(03)00070-3

UNISDR, 2021. Inventar [WWW Document]. Desaster Inf. Syst. URL http://www.desinventar.lk:8081/DesInventar/ (accessed 5.14.21).

Vannoppen, W., Vanmaercke, M., De Baets, S., Poesen, J., 2015. A review of the mechanical effects of plant roots on concentrated flow erosion rates. Earth-Science Rev. https://doi.org/10.1016/j.earscirev.2015.08.011

Visser, S., Keesstra, S., Maas, G., de Cleen, M., Molenaar, C., 2019. Soil as a basis to create enabling conditions for transitions towards sustainable land management as a key to achieve the SDGs by 2030. Sustain. 11, 6792. https://doi.org/10.3390/su11236792

Wang, Z., Hou, Y., Fang, H., Yu, D., Zhang, M., Xu, C., Chen, M., Sun, L., 2012. Effects of plant species diversity on soil conservation and stability in the secondary succession phases of a semihumid evergreen broadleaf forest in China. J. Soil Water Conserv. 67, 311–320. https://doi.org/10.2489/jswc.67.4.311

Waring, R.H., Coops, N.C., Fan, W., Nightingale, J.M., 2006. MODIS enhanced vegetation index predicts tree species richness across forested ecoregions in the contiguous U.S.A. Remote Sens. Environ. 103, 218–226. https://doi.org/10.1016/j.rse.2006.05.007

Warren, S.D., Alt, M., Olson, K.D., Irl, S.D.H., Steinbauer, M.J., Jentsch, A., 2014. The relationship between the spectral diversity of satellite imagery, habitat heterogeneity, and plant species richness. Ecol. Inform. 24, 160–168. https://doi.org/10.1016/j.ecoinf.2014.08.006

Wessels, K.J., Prince, S.D., Malherbe, J., Small, J., Frost, P.E., VanZyl, D., 2007. Can human-induced land degradation be distinguished from the effects of rainfall variability? A case study in South Africa. J. Arid Environ. 68, 271–297. https://doi.org/10.1016/j.jaridenv.2006.05.015

Wessels, K.J., Prince, S.D., Reshef, I., 2008. Mapping land degradation by comparison of vegetation production to spatially derived estimates of potential production. J. Arid Environ. 72, 1940–1949. https://doi.org/10.1016/j.jaridenv.2008.05.011

Wessels, K.J., van den Bergh, F., Scholes, R.J., 2012. Limits to detectability of land degradation by trend analysis of vegetation index data. Remote Sens. Environ. 125, 10–22. https://doi.org/10.1016/j.rse.2012.06.022

Wickramagamage, P., 1998. Large-scale deforestation for plantation agriculture in the hill country of Sri Lanka and its impacts. Hydrol. Process. 12, 2015–2028. https://doi.org/10.1002/(sici)1099-1085(19981030)12:13/14<2015::aid-hyp716>3.0.co;2-3

Yang, X., Zhang, M., Oliveira, L., Ollivier, Q.R., Faulkner, S., Roff, A., 2020. Rapid assessment of hillslope erosion risk after the 2019–2020 wildfires and storm events in sydney drinking water catchment. Remote Sens. 12, 1–20. https://doi.org/10.3390/rs12223805

Yengoh, G.T., Dent, D., Olsson, L., Tengberg, A.E., Tucker, C.J., 2014. The use of the Normalized Difference Vegetation Index (NDVI) to assess land degradation at multiple scales: a review of the current status, future trends, and practical considerations, SpringerBriefs in Environmental Science. Springer International Publishing, Cham. https://doi.org/10.1007/978-3-319-24112-8