remote sensing

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Review

A Review on Assessing and Mapping Soil Erosion Hazard Using Geo-Informatics Technology for Farming System Management

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Abstract: Soil erosion is a severe threat to food production systems globally. Food production in farming systems decreases with increasing soil erosion hazards. This review article focuses on geo-informatics applications for identifying, assessing and predicting erosion hazards for sustainable farming system development. Several researchers have used a variety of quantitative and qualitative methods with erosion models, integrating geo-informatics techniques for spatial interpretations to address soil erosion and land degradation issues. The review identified different geo-informatics methods of erosion hazard assessment and highlighted some research gaps that can provide a basis to develop appropriate novel methodologies for future studies. It was found that rainfall variation and land-use changes significantly contribute to soil erosion hazards. There is a need for more research on the spatial and temporal pattern of water erosion with rainfall variation, innovative techniques and strategies for landscape evaluation to improve the environmental conditions in a sustainable manner. Examining water erosion and predicting erosion hazards for future climate scenarios could also be approached with emerging algorithms in geo-informatics and spatiotemporal analysis at higher spatial resolutions. Further, geo-informatics can be applied with real-time data for continuous monitoring and evaluation of erosion hazards to risk reduction and prevent the damages in farming systems.

Keywords: soil erosion; hazard; farming systems; GIS; remote sensing

1. Introduction

Soil erosion is a natural phenomenon. Intensification of soil erosion causes environmental, economic and social disturbances and hazardous situations [1]. It deteriorates the soil quality: loss of nutrients [2], changes in physical, chemical and biological processes [3] and reducing agriculture productivity [4] resulting in global food insecurity [5]. Human interference and climate variation lead to the intensification of soil erosion [6]. Many studies show that agricultural landscapes, mainly farming systems, are more vulnerable to soil erosion due to present climate variation [7,8]. Keating and McCown [9] described the farming system as an entire production system and management system on a particular farm or similar farms. The Food and Agriculture Organization defined the farming system as “a population of individual farm systems that have broadly similar resource bases, enterprise patterns, household livelihoods and constraints and for which similar development strategies and interventions would be appropriate. Thus a farming system can encompass a few dozen or many millions of households” [10]. When the erosion rate is accelerated beyond the level of the permissible rate, it leads to a hazard. Rahman et al. [11] defined a hazard as “a threatening situation to human life, property or environment.” The soil erosion hazard influences the landscape processes such as land productivity, hydrological processes and eventual human wellbeing. Therefore, soil erosion assessment is important in understanding landscape processes. However, soil erosion assessment is highly complex due to its multifactorial influences [12,13]. This complexity is reflected in the huge number of publications pertaining to the subject. Hence, climatic, biophysical, topographic and human interference (such as socio-economic and political factors) are needed to be considered for soil erosion assessment.

Since the 1930s, several soil erosion models have been developed and tested; however, it is still challenging for researchers to assess and predict soil erosion accurately due to its complex nature [3,14]. Karydas et al. [15] have identified 82 soil erosion models and classified them under eight geospatial categories. They identified the integration of geospatial techniques as a landmark change for the soil erosion assessment. In recent decades, soil erosion assessment integrated with geospatial technology has enabled the development of simplified models to assess complex situations. Geo-informatics is a field of study on the scientific investigation of economic, social, environmental, health & safety and security challenges in multiple disciplines by analyzing big geospatial and temporal data and interpretation of results for better understanding and decision-making [16]. It is widely applied in various disciplines of engineering, earth science, climate science & meteorology, agriculture, public health, archaeology, oceanography, military and so forth. The geo-informatics helps in the acquisition of different types of data on socio-economic and biophysical parameters using geospatial technology—geographic information systems (GIS), remote sensing (RS) and global positioning systems (GPS). It also facilitates data storage, management, analysis and visualization to develop new theories and methodological tools to address complex social and environmental challenges. Geo-informatics has great potential for soil erosion assessment [17] and benefited for combining soil erosion modelling in recent past.

This review paper examines previous research methodologies and findings related to the geo-informatics applications addressing soil erosion hazards from a wide range of sources: high-quality journal articles, internet sources, books. In this context, this paper aims to address the research question on “how geo-informatics technology has been applied to assess and reduce the impact of soil erosion hazards in a study area.” This review identifies gaps in knowledge in order to answer the research question and guide sustainable landscape solutions. The review is organized as follows: a brief description of what a soil erosion hazard is and modelling of soil erosion and determinants of water erosion. The review then provides an overview of advancements in geo-informatics technology in the context of soil erosion, spatial and temporal detection and prediction, gully erosion susceptibility mapping and management strategies. Then challenges, innovations and future directions are discussed. The paper is finally concluded with implications for future research.

2. Soil Erosion Hazards

Soil erosion by water, that is, “water erosion” has been identified as the major threat to the agriculture landscape and farming systems [18,19]. Water erosion in farmlands reduce the crop yield and change the land-use patterns that may induce a risk of food insecurity [20,21]. Water erosion greatly contributes to the soil erosion hazard [6,13]. Hazard is a situation or potential condition to harm or threat to life, health or damage to property or environment [22]. Researchers revealed increasing rainfall intensities and prolong seasonal dry periods due to climate variation have triggered an intensification of soil erosion and temporal probability of hazard occurrence such as mass movements [23]. The extent, frequency and magnitude of the soil erosion and its associated temporal probability of occurrence can be increased due to future climate change [8,24]. The anthropogenic factors such as land use change and forest fires further exacerbated the soil erosion hazard situation [23,25]. Moreover, water erosion caused by environmental hazards was reported by many scholars with the main cause being highland developments in the recent past [1,26,27].

The mass movement of soil is an indicator of a soil erosion hazard. This includes gully erosion, riverbank erosion, rock-falls, debris-falls and landslides that can create damage to the environment and livelihoods. Annually, more than thousands of lives are lost due to mass soil movement worldwide [28]. However, Blaschke et al. [29] revealed that impacts of mass movement on soil erosion and land productivity are under-rated in the literature. Thus, less research attention was given on soil erosion due to the mass movement. Most of the soil erosion hazards prevail during a rainy season or after heavy rain [17,30]. Mostly, the tropical agricultural lands are vulnerable to gully erosion and landslides due to heavy water erosion [1,31]. Researchers have identified that landslides and other types of mass movement are responsible for losses of thousands of lives and hundreds of millions of US dollars' worth of property and agricultural losses every year [32]. Therefore, understanding the potential risk or susceptibility to soil erosion is very important for mitigation and risk minimization.

Several studies have highlighted sediment deposition in water sources and its impact on water quality, biodiversity and natural resources [31,33]. Wilkinson et al. [34] have pointed out that understanding of driving factors of gully initiation and assessing water erosion dynamics in the river basin of northeast Australia is important due to its influence on Great Barrier Reef lagoon. Therefore, it is vital to estimate flow discharge and corresponding erosion rates on steep-slope lands using realistic runoff and water erosion models. This information is needed to map for conserving natural resources, prevention and control soil erosion by aiming sustainable land management process [35]. Furthermore, Poesen [6] highlighted more research is needed on soil erosion runoff and sediment deposition with hydrological response related to present rainfall variation on sloping lands in order to identify better conservation plans.

2.1. Modelling of Soil Erosion

The natural soil erosion process is induced due to heavy rainfall, runoff, drought, snowfall, wind, fire and gravity. Soil erosion by water is the most significant factor of land degradation [14,36,37]. Water erosion can be observed throughout the world as one of the most important factors that can induce mass soil movement. For instance, United States' agricultural lands are having an average annual water erosion 5–170 t ha^{-1} yr^{-1}, China 150–200 t ha^{-1} yr^{-1}, Australia 0.1–150 t ha^{-1} yr^{-1}, India 0.3–40 t ha^{-1} yr^{-1}, Belgium 3–30 t ha^{-1} yr^{-1}, Ethiopia 8–42 t ha^{-1} yr^{-1}, Colombia 0.2–61 t ha^{-1} yr^{-1}, Brazil 60 t ha^{-1} yr^{-1} Europe 2.46 t ha^{-1} yr^{-1} and Rassia 4.58 t ha^{-1} yr^{-1} [17,32,38,39].

The tolerable threshold value of soil erosion depends on soil production functions that maintains by ecosystem service. Therefore, the rate of soil production varies with different regions [40]. Borrelli et al. [25] revealed generic tolerable soil erosion threshold value is 10 t ha^{-1} yr^{-1}. However, the tolerable value of range between 4.5 and 11.2 t ha^{-1} yr^{-1} was proposed by the work of United States Department of Agriculture. The European Environment Agency sets the threshold value between 1 t ha^{-1} yr^{-1} for shallow sandy soils and 5 t ha^{-1} yr^{-1} on deeper, well-developed soils. Bui, Hancock and Wilkinson [41] provided value of 0.85 t ha^{-1} yr^{-1} for Australia as reported by Food and Agriculture organization [40].

Research supports the assumption that rainfall accelerates soil erosion in hilly areas and watersheds because soil erosion is highly sensitive to precipitation [38,42]. The process of water erosion consists of detachment, transportation and deposition of sediment in a separate place [3,43,44]. There are several types of water erosion such as splash erosion, sheet or inter-rill, rill, gully or ravine [31,45]. Figure 1 shows the types of soil erosion by water. The kinetic energy of water drops detaches the soil surface into soil particles, which are known as splash erosion. These soil particles move with runoff water flow. These runoff water flows create tiny channels (rills) in hill slopes. When these water flows of rills connect, they cause the formation of gullies. This process can be described as gully erosion. The removal of soil layers is called sheet erosion. The rate of soil erosion depends on several key factors such as rainfall intensity, soil infiltration, amount of runoff water and slope length [46]. However, soil erosion may depend on some other factors such as anthropogenic activities as well. It is important to understand the process of soil erosion and its impacting factors in order to select an effective method for monitoring water erosion in the context of sustainable land management.

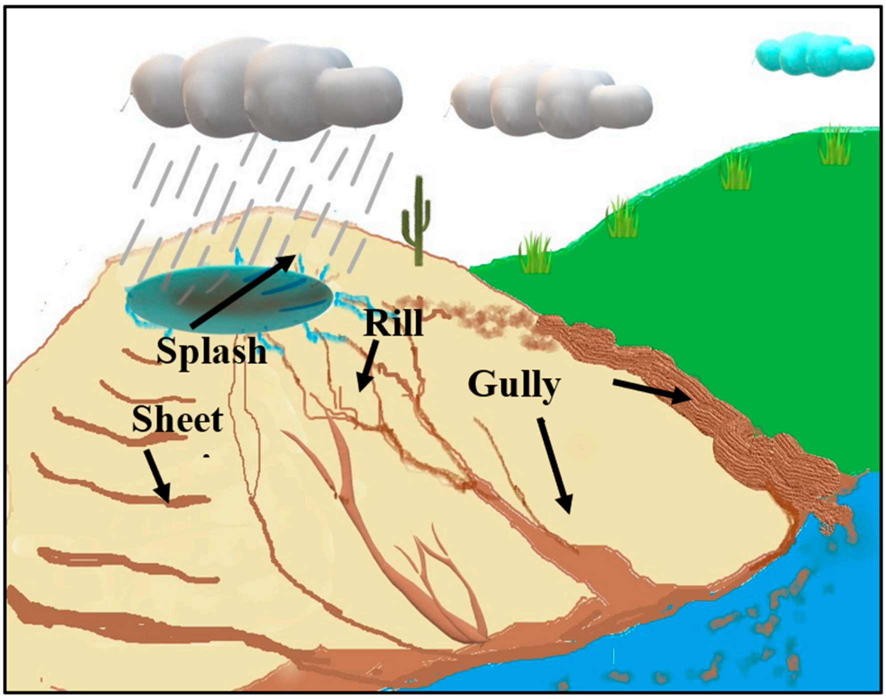

Figure 1. The types of soil erosion by water.

Water erosion assessment methods can be categorized into three main approaches: (i) the field plot experiment or fallout radionuclides methods using average soil loss measurements [47], (ii) the field survey method by visible soil erosion indicators and identification of soil erosion influencing factors [48] and (iii) soil erosion modelling [44]. The classification of soil erosion assessment methods shows in Figure 2. Soil erosion assessment using field experiments was done by many researchers over several decades [47,49]. Most of the methods were executed as field plot scale or watershed base experiments. Poesen [6] identified hydrological discharge on the hill slopes or catchments are dependent on the area and cannot generalize from a field plot experiment. The realistic runoff should be measured according to the relief and corresponding erosion rates on hill-slopes. These understandings of soil erosion runoff are important for better predicting sheet and rill erosion rates in different environments. Ganasri and Ramesh [50] indicated that most of these conventional methods of soil erosion assessments are expensive and time-consuming. However, soil erosion modelling approaches provide a quantitative and reliable estimation for the erosion process and sediment yield in a diverse environment [50,51].

Numerous soil erosion models have been developed by utilizing different scientific methods and modelling approaches. In general, three categories of soil erosion model based on the nature of the basic algorithms exist (a) physics-based, (b) empirical and (c) conceptual models [31,42]. These three categories of soil modelling will be discussed briefly in the following sections.

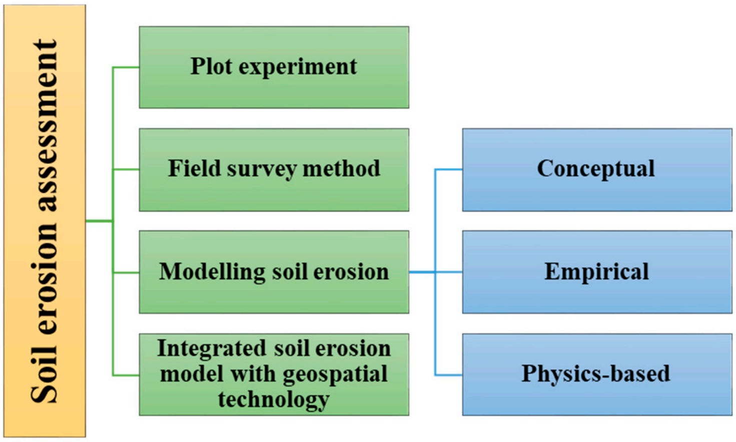

Figure 2. Classification of soil erosion assessment methods.

2.1.1. Physics-Based Models

Physics-based models are built on field-based research and simulate climate, runoff, infiltration, water balance, plant growth and decomposition, tillage and consolidation. These models are on the basis of the physics of flow and sediment transport processes and their interaction on the transfer of mass, momentum and energy [52]. It can be applied for a range of experiments such as from a field plot scale to small watersheds and different time periods, including individual storm events, monthly, yearly or an average annual value, based on the data from several decades. Major limitations of these models are high complexity and computational costs. The Water Erosion Prediction Project (WEPP) model is an example of a commonly used physical process-based water erosion model [53]. It was developed as a system modelling approach for predicting and assessing soil loss and identifying watershed management practices for soil conservation.

2.1.2. Empirical Models

Empirical models are simplified natural processes based on experimental observations. Argent [54] explained the models that calibrate the relationship between input and output without a detailed description of the causes of each process. These equations are based on observations of the environment that can be statistically quantified and proven [55]. Hence, empirical models are frequently employed for soil erosion modelling and useful for identifying the sources of sediments and quantifying the erosion rates [56]. Empirical-based models have been widely used in soil erosion assessments. The Universal soil loss equation (USLE), the revised universal soil loss equation (RUSLE) and modified universal soil loss equation (MUSLE) are commonly employed empirical-base models Equation (1) for soil erosion assessments [57,58]. Tiwari et al. [59] compared runoff and soil loss amounts by RUSLE and WEPP models. They found RUSLE and WEPP models satisfactorily predicted soil loss for the analyzed conditions and RUSLE performance was better than WEPP.

$$A = R \times K \times LS \times C \times P. \tag{1}$$

A—Average annual soil erosion rate in soil mass per unit area per year (t ha^{-1} $year^{-1}$).
R—Rainfall erosivity factor (MJ mm ha^{-1} h^{-1} yr^{-1}),
K—Soil erodibility factor (t ha h MJ^{-1} mm^{-1}),
LS—Slope length and steepness factor (dimensionless),
C—Crop management factor (dimensionless)
P—Land management factor (dimensionless).

2.1.3. Conceptual Models

Conceptual models are a combination of empirical and physical-based models. General descriptions of catchment processes can incorporate to conceptual models without stipulating process interactions, since detail catchment information would require for process interactions [56]. Therefore, conceptual models provide measurements on quantitative and qualitative processes within an area such as a watershed and consist with inherent limitations of empirical models such as a wide range of data set are needed for calibration. The conceptual soil erosion model AGNPS (agricultural non-point sources pollution model) that combines SCS (Soil conservation service) method and RUSLE that predicts runoff with SCS and soil erosion loss. The SWAT (soil and water assessment tool) model predicts runoff with SCS curve number and MUSLE for soil loss prediction [43].

Despite the above three categories of soil erosion modelling, recent studies have introduced several new approaches on the model application and scenario-based simulations to predict the impacts of land use and climate change on soil erosion. A combined approached of LTM (Artificial Neural Networks algorithm- ANN), SCS-CN model and ARUMA has been applied to soil erosion assessment by Rizeel et al. [60]. Arambarani et al. [61] have employed AHP and multi-criteria decision-making approach in the GIS environment to investigate the erosion-prone areas. LTM together ANN with and USLE models have been used to predict soil erosion and land cover dynamics [13]. Weights-of-evidence (WoE) and evidential belief function (EBF) models were used by Gayen and Saha [62] to identify the soil erosion in vulnerable areas. Another recent study employed ANN, geographically weighted regression (GWR) and GWR–ANN ensemble model to predict soil erosion [63].

2.2. Determinants of Water Erosion

Water erosion accelerates on several factors such as rainfall, topography, soil susceptibility, slope characteristics, crop factors and land management practices. Wischmeier and Smith [44] identified that soil erosion depends on several key factors—rainfall kinetics, slope length and steepness factor, crop and management factor. In addition, snow covers the surface of land area in winter and spring seasons, at most part of arable land of the humid plains in the temperate zone. Hence, the soil contains wet condition and makes it more vulnerable for the erosion due to repeated freezing and melting [53]. Further to this, more soil erosion occurs with less ground cover areas due to snowmelt runoff, usually during the late winter or spring [64]. The permeability of the surface soil increases due to repeated freezing and melting that enhance more soil erosion [65]. Researchers have also been widely considered various other factors for modelling such as land-use change, lithology, distance to river and distance to the road. The following sections discuss key factors affecting water erosion in detail.

2.2.1. Rainfall

The capability of rainfall to cause soil erosion is defined as the erosive power of rainfall or rainfall erosivity. It has been observed that rainfall amount, intensity and spatiotemporal distribution may vary with climate variation [24–66]. Besides, irregular and intense precipitation is the leading cause of water erosion [67,68].

Several attempts have been made to study the impact of rainfall intensity and rainfall patterns on soil erosion such as surface ceiling, runoff water, erosion hazard, loss of organic matter and soil fertility. Studies have shown that rapid changes take place during rainfall, affecting infiltration and runoff in the erosion processes [69,70]. The increasing of rainfall reduces the nutrient level [5] and enhances the acidification in the soil.

Almagro et al. [71] have reported warm climates, temperature and intense rainfalls will increase significantly due to an increase of global mean temperature from one degree Celsius. As a result, the moisture retention capacity of the atmosphere will increase by 7%. Water vapor in the atmosphere influences the circulation patterns of the hydrological cycle and initiates high intensity and extreme rainfall events [72]. In a recent paper, Poesen [6] highlighted that more research should be done on rainfall characteristics such as rainfall amount, rainfall intensity, rainfall depth, erosivity and a number of rainy days with present climate variation in different regions. For example: in Europe, researchers have predicted that a relative mean rain erosivity may increase by 18% in 2050 (compared to 2010) due to large spatial variability of rainfall [73]. Hence, understanding the impact of the extreme situations of precipitation is important and it can be used to study rainfall erosivity and soil erosion for shorter time intervals.

The expansion of erosion features based on precipitation events can also be examined through high temporal resolutions. Hence, more research is needed for investigation on rainfall variation in hill-slope against various crop management practices with present rainfall variation. Special attention should be paid to soil erosion hazards caused by physical changes in the soil due to rainfall variation.

2.2.2. Slope Length and Steepness

Terrain characteristics such as slope steepness and slope length play a major role in soil loss [74,75]. In a hilly area, when the slope length increases, soil runoff in the downslope direction per unit area also increases. While the slope steepness increases, the runoff velocity is increased. When the slope increases, runoff water will find a path nearby increasing soil erosion and reducing infiltration [50]. The slope length and steepness would increase the velocity of runoff by reducing infiltration, which causes severe damage to the soil as well as livelihoods. The ground cover from plants or mulch helps to reduce the runoff velocity. Hence, it is vital to make policy changes on land-use and soil conservation measures to minimize the severity of damages in terms of the effect of rainfall variation in hillslopes.

2.2.3. Soil Erodibility

Soil erodibility reflects the soil susceptibility to erosion. Mainly, it depends on the organic matter content, soil texture (silt, very fine sand, sand and organic matters), permeability and aggregate stability [76]. Soil erodibility values for different types of soil can be obtained from nomographs [44]. However, runoff plots under the standard conditions of fallow soil is a reliable way to measure the soil erodibility for local soil types. Studies should be carried out for a period of more than five years to obtain satisfactory values from field plot experiments [77]. Hence, researchers commonly assumed that once the soil erodibility value has been established for the soil in a particular area, this soil erodibility value is permanent. Nonetheless, Poesen [6] has indicated that soil erodibility depends on climate variation and it was not fully recognized. Therefore, more research is needed to study rainfall variation, topography and vegetation impacts on soil erodibility.

2.2.4. Ground Cover

Vegetation cover helps to protect the soil from the disintegration of soil particles by rainfall and acts as a barrier for the detachment of soil particles [78,79]. Hence, if vegetation cover is large enough, the impact of the rainfall will reduce the erosion rate. Plant root systems also play a significant role in soil erosion, where the above-ground mass is not prominent due to grazing, drought or fire. A major contribution from a plant root system for the erodibility is the ability of mechanical soil binding. Although plant roots do not have a prominent effect on splash erosion, some plants have better-rooting patterns, so they hold the soil in better and prevent the formation of rills, gully and shallow landslides [80,81]. Therefore, Poesen [6] suggests that more attention should be given to examining the effect of root characteristics and soil erosion rates in different soil types.

2.2.5. Conservation Practices

Water erosion leads to land degradations in farming systems and low productivity of crop production. Soil and water conservation structures help to reduce the water erosion [82], increase the soil moisture, soil fertility and improve a response to commercial fertilizer that contributes to increase crop yield [83]. According to Udayakumara et al. [84], soil conservation measures improve soil health and help to improve the ecosystems services in every aspect. Agricultural practices, such as multiple cropping and agroforestry, also increase soil organic matters and soil carbon sequestration. Thus, multiple cropping and agroforestry practices reduce the soil erosion through cover crops, deep-rooted crops and verities [85,86]. Poor crop management practices are directly related to inducing water erosion. This situation can be improved by implementing crop management strategies, such as planting cover crops, minimum tillage and adding organic matter to enhance water infiltration through improving the availability of soil moisture [87]. In addition, these strategies may also help to mitigate the impacts of severe rainfall and drought events or from water erosion [88,89].

This review highlights several models that have been employed by researchers to monitor factors of water erosion. Researchers have made huge progress in the process of soil erosion, identifying the causative factors and its controlling mechanisms through modelling approaches. The USLE [44] and RUSLE [90] are widely employed to assess long-term soil erosion rates from farmlands due to different management practices [57]. Several studies have analyzed soil erosion and soil erosion hazards in different agricultural sloping lands using the models of USLE and RUSLE around the world. Although empirical models do not tend to be event responsive, instead they estimate soil erosion annually.

Integration of different models is used to identify and estimate soil erosion and soil erosion hazard vulnerability in recent literature. Initially, USLE/RUSLE models had limitations with spatial distribution, which have been overcome by integrating geo-spatial technology [57]. In this context, geo-informatics played a vital role in advanced methodological development in estimating soil erosion and soil erosion hazards [91].

3. Advancement of Geo-Informatics Technology in Soil Erosion Research

The geo-informatics technologies, that is, remote sensing, geographic information system (GIS) and global positioning system (GPS) have been integrated with various soil erosion models for soil erosion assessment and risk evaluation [11]. Many studies have been conducted using different soil erosion models combined with geo-informatics techniques [1,37,50,91,92]. The capabilities of geo-informatics such as efficient data collection, analysis and validation techniques, provide valid information on dynamics and intensity of soil erosion over the time and space for controlling and forecasting [57,93,94]. Brits et al. [95] believe that the use of geo-informatics technology has been widely expanded due to its rapid development and capabilities with new tools and software. The application of geo-informatics to soil erosion studies has been popularized as a robust, low cost and high accuracy method [92]. It offers a significant strength for soil erosion assessment at a larger spatial scale, particularly where difficulty in reaching field investigations [57]. Soil erosion assessments have been conducted based on different territorial units of spatial analysis (raster grid basis) such as watershed or river basin, country, regional and global scale levels. Most parameters of water erosion are scale- dependent. For example: a smaller geographical scale (plot experiment) mostly uses to study on-site impacts of soil erosion while a larger geographical scale employs to investigate on off-site impacts of soil erosion. Because the same scale is not always, appropriate for realistic soil erosion assessments [15].

The remote sensing-based airborne and space-borne sensors such as multi-spectral, hyperspectral, Radio Detection and Ranging (RADAR) and Light Detection and Ranging (LiDAR) and their wide range of applications have been used to detect soil erosion in different scales of landscape throughout the world. The remote sensing platforms for soil erosion hazard assessment is illustrated below in Figure 3. Das et al. [96] described that these methods could be used on rapid assessments without disturbing the soil surface and have vast spatial coverage. In addition, these technologies help for a sequence of a time-period assessment with a less cost [92]. Although high spatial resolution satellite imagery such as IKONOS, QuickBird and Spot 5 are in high cost, coarse resolution satellite imagery: Landsat, Moderate Resolution Imaging Spectrometer (MODIS), National Oceanic and Atmospheric Administration Advanced Very High-Resolution Radiometer (NOAA-AVHRR) and Advance Space-borne Thermal Emission and Reflectance Radiometer (ASTER) are freely available for researchers and can be utilized for the time series analysis. A summary of temporal and spatial resolution is given in Table 1.

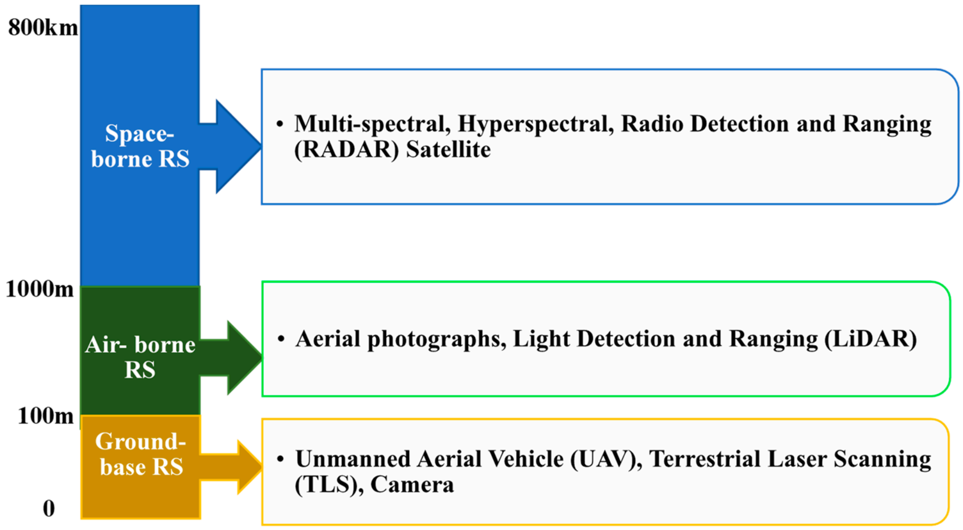

Figure 3. Remote sensing platforms for soil erosion hazard assessment.

Table 1. Summary of temporal and spatial resolution adapted from Reference [97].

Satellite	Temporal Resolution	Spatial Resolution
IKONOS	24 h	0.82 m panchromatic; 3.28 m multispectral,
QuickBird	3.5 days	2.4 m spatial resolution and a panchromatic band at a 0.6 m
Spot 5	26 days	2.5 to 5 m in panchromatic mode and 10 m in multispectral mode
Landsat 3–8,	16 days	15 m panchromatic 30 m multispectral
MODIS	1–2 days	250 m at nadir, with five bands at 500 m, provides global coverage
NOAA-AVHRR	twice per day	1.1 km
ASTER	6 days at the equator	60 km
Sentinel-2A	5 days	10–60 m

The majority of satellite image sources have a limitation with accurate surface reflectance retrieval. Thus, land cover change detection is limited. A number of radiometric correction techniques have been developed to address this limitation [98]. In contrast, NASA's Earth Observing System (EOS) and Moderate Resolution Imaging Spectroradiometer (MODIS) are equipped with surface reflectance products for land cover change detection [99]. Further to this, the availability and low cost of images are major benefits of Landsat series data. Hence, Landsat data can be used for long term monitoring purposes. However, there are several limitations with Landsat series data: the low spectral resolution of the sensor and limited capability of soil erosion parameters estimation such as vegetation cover, outlining of bare surfaces, calculation of vegetation indices and change of topography [100]. Nevertheless, Sentinel 2 and Landsat 8 series data provide improved spatial, spectral radiometric and temporal resolutions as a most required spatial tool for continuous monitoring [57].

The vegetation indices have been identified as a simple and quick feature extraction technique for soil erosion by assessing and mapping from satellite data [57]. A number of researchers have suggested that soil erosion classes could be delineated based on vegetation cover interpretation and multi-temporal images allow to assess its expansion [101,102]. Research shows that vegetation cover is depressed with the occurrence of land degradation [79]. The vegetation indices, such as Normalized Difference Vegetation Index (NDVI) have been used for many studies of soil erosion [57,68,84,103]. NDVI is a vegetation index derived base on remote sensing techniques mostly apply with above-ground net productivity and dynamics with spatial and temporal distribution of vegetation cover [104]. This index can be used to obtain information about not only plant growth characteristics but also site-specific qualities such as prevailing climate, ecosystem, terrain and physical soil properties [105,106]. Puente et al. [68] have indicated that NDVI is a commonly used vegetation index for extraction of the vegetation information from satellite data. This index identifies healthy and green vegetation. A number of studies have been examined soil erosion patterns by analyzing the changes of NDVI values using time series analysis in growing seasons and onset of the dry seasons [103,107]. In addition, the soil properties have been studied by several researchers using NDVI images, that is, soil color [108,109], soil texture and water holding capacity [107], root zone soil moisture [110] and soil carbon and nitrogen content [106].

The digital elevation model (DEM) is one of the essential inputs required for soil erosion modelling, which can be generated by analysis of remotely sensed spectral data such as stereoscopic optical (ASTER), microwave (synthetic aperture radar-SAR), Shuttle Radar Topography Mission (SRTM) and terrestrial LiDAR for 3D representation in a various resolution for landform recognition [24,111]. The radar has the capability of penetrating through the canopy cover and is independent from weather and daylight to retrieve high resolution remotely sensed data [112]. LiDAR can produce high-resolution topographic data, which can be used to generate Digital Terrain Models (DTM) and Digital Surface Models (DSM) for detail terrain analysis [113].

There are several global geospatial databases available for soil erosion assessments. Global Historical Climatology Network-Daily provides global daily rainfall data [114]. GTOPO30 provides digital elevation model (DEM) with resolutions of 1000, 500 and 250 m [115]. Global soil degradation data are available at GLASOD [116] and GLADIS [25,117]. Data of land degradation in dryland areas can be accessible in LADA of FAO, UNEP-GEF [117]. However, these models have limited predictive power due to coarse resolution [25].

The value of NDVI may deviate due to noises in the satellite data due to cloud cover, water, snow, shadow, sources of errors, false highs or scan angles or transmission errors [118]. Hence, the soil-adjusted vegetation index (SAVI) [119], the Transformed SAVI (TSAVI) [120], the Modified SAVI (MSAVI) and the Global Environment Monitoring Index (GEMI) [121,122] are used to reduce soil background reflectance. Furthermore, the Enhanced Vegetation Index (EVI) can be used to minimize the contamination problems of NDVI images (canopy background and residual aerosol influences) and provides complementary information about the spatial and temporal variation of the vegetation cover [121]. The most popular general equations for vegetation indices are summarized in Table 2.

Table 2. Summary of vegetation indices.

Vegetation Index	Equation Formula	Reference
NDVI	$\mathrm{NDVI} = \frac{(NIR-RED)}{NIR+RED}$	[123]
SAVI	$\mathrm{SAVI} = \frac{(NIR-RED)(1+L)}{NIR+RED+L}$ where L = correction factor between 0 and 1	[119]
EVI	$\mathrm{EVI} = G\frac{(NIR-RED)}{(NIR+C1.\ RED-C2.\ B+L)}$ G = 2.5; C1 = 6; C2 = 7.5; L = 1	[123]
	$\mathrm{TSVI} = \frac{s(NIR-sRED-a)}{(aNIR+RED-as+X(1+s2)}$ s = the soil line slope a = the soil line intercept X = an adjustment factor that is set to minimize soil noise	[120]
MSAVI	$\mathrm{MSAVI} = \frac{(2*\mathrm{NIR}+1-\mathrm{sqrt}\ ((2*\mathrm{NIR}+1)2-8*(\mathrm{NIR}-\mathrm{R})))}{2}$	[122]
TSAVI	(2)	[120]

Recent research studies have claimed that rainfall and land-use change play a major role in soil erosion hazard of different regions [124,125]. Rainfall data is crucial for several applications such as soil erosion assessment, risk evaluation and forecasting [126]. There are also satellite sensors that can provide spatially contiguous soil moisture data (soil moisture active passive (SMAP) or advanced scatterometer (ASCAT)) and spatial rainfall data [127]. The dynamic of land use and land cover can be studied using space and airborne imageries [128] with different classification methods. Yang et al. [129] reviewed landscape classification systems and realized that these classification systems were important to understand the landscape patterns and changes for cross-comparison or validation. The satellite image classification algorithms can be categorized as supervised, unsupervised and hybrid methods (Figure 4). Recently, advanced non-parametric classifiers such as Neural Network, Regression tree, Fuzzy set classification logic, Support Vector Machines (SVM) and Mahalanobis distance classifier (MDC) have been used over the traditional parametric classification methods [111]. Moreover, Terrestrial laser scanning (TLS) method can be applied for a variety of applications such as land-use changes [130,131], landslide susceptibility, rock-fall [132] and gully erosion assessment [133]. GIS-based TLS provides an accurate method for collecting much higher density dataset [130]. Temporal comparison has also been used to find changes (enlargement) of eroded lands by using satellite data (Landsat TM) and aerial photos [134]. Individual features such as gullies and large rills can be identified by using satellite data. However, there are limitations with satellite data due to clouds and canopy covers. Hence, aerial photography is a common method for detecting individual gullies as it provides better differentiation [97].

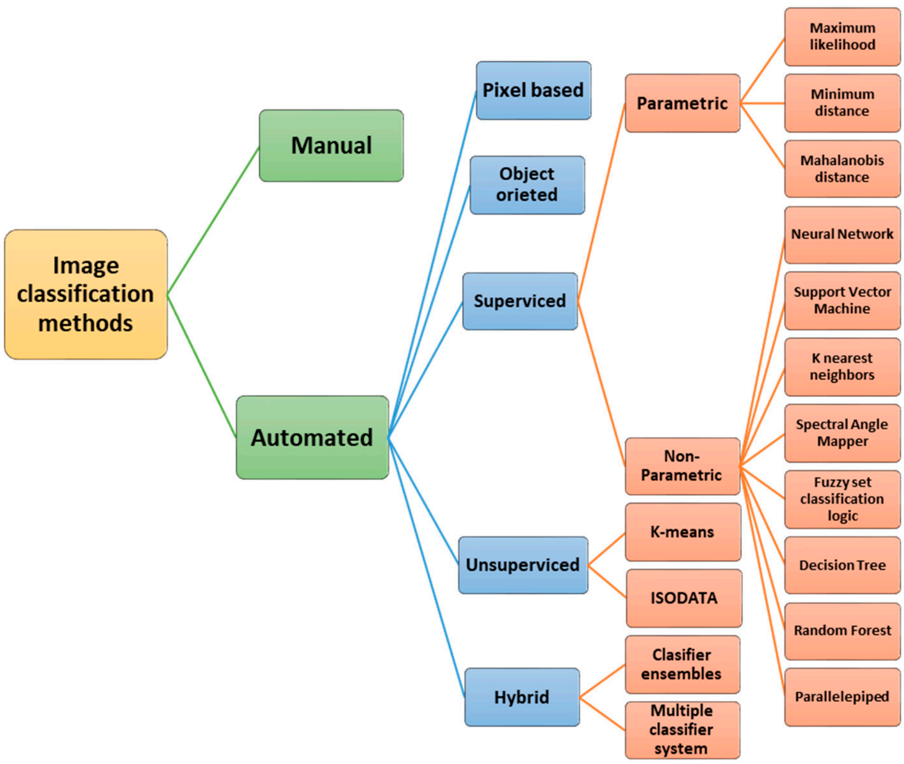

Figure 4. Image classification methods for land-use change detection and soil erosion hazard assessment.

Unmanned Aerial Vehicles (UAV) derived data is becoming more popular due to its rapid development in sensor technology [135], low cost and risk [113,136]. The UAV-based LiDAR and hyperspectral images provide much more detailed estimates of earth surface processes and patterns for geomorphological and hydrological modelling, including soil erosion estimate and river channel morphology changes [137]. In addition, UAV well performs in DTM, biodiversity monitoring and land-cover change detection [138]. UAV data can be used to deriving vegetation indices such as NDVI, which are correlated with biophysical characteristics of vegetation cover [139,140].

The integrated use of remote sensing, GIS and soil erosion modelling has been widely applied by researches for soil erosion assessment. Table 3 provides a few examples of recent research on integrating remote sensing-based soil erosion assessment in a GIS environment.

Table 3. Integrated soil erosion modelling approaches with remote sensing-based methods.

Soil Erosion Model	Remote Sensing-Based Methods	Data Sources	Study Area	Reference
RUSLE	Normalized Difference Vegetation Index (NDVI) for vegetation cover	Multi-source remotely sensed data (MODIS, Gaofen (GF)-1)	China	[141]
RUSLE	Land use/land cover classes generation	Indian remote sensing (IRS) satellite 1D-LISS-3 image	India	[50]
Soil plots and RUSLE	Digital erosion Model (DEM) Rainfall depths and intensity Ground cover	Light Detection and Ranging (LiDAR) and Shuttle Radar Topography Mission (SRTM)-radar rain-field data in NetCDF, Landsat-8 imagery Rapideye, Aerial photograph	Australia	[76]
USLE	Land use/cover classification for C-factor generation using Supervised classification	SPOT 5 and Landsat ETM+	Malaysia	[1]
RUSLE and Land-use change	Object-based image classification for land-use land cover change detection	SPOT-5	Malaysia	[142]
Field plot method	Normalized Difference Vegetation Index (NDVI) for vegetation cover	ALOS data	Sri Lanka	[84]
Analytical hierarchy process (AHP)	NDVI Different land use/land cover classification	IRS-P6 LISS III	China	[14]
Biophysical factors derivation	Vegetation cover, DEM and topographic variables (slope, stream erosivity-SPI, topographic wetness index TWI)	Landsat TM images ASTER DEM	South Africa	[92]
USLE	Land transfer model (LTM)	Spot 5	Malaysia	[13]
RUSLE and Sediment yield	Normalized Difference Vegetation Index (NDVI) for C-factor generation	Landsat images (TM)	Iran	[143]
Gully erosion detection	Normalized Difference Vegetation Index (NDVI) for vegetation cover	Unmanned Aerial Vehicles (UAVs)	Morocco	[144]

Many researchers used remote sensing and GIS tools to monitor, mapping and forecast soil erosion hazard and land-use/land-cover changes [13,145]. In addition, geo-informatics technology provides a better understanding of spatio-temporal relationship in soil erosion hazards, that is, gully erosion susceptibility mapping and landslide vulnerability mapping. The spatial and temporal distribution of hazards are important to assess the causative factors, vulnerability and to study its correlation with future incidents. The recent works of soil erosion assessment at a global scale have provided new knowledge about future soil erosion rate and prediction. Borrelli et al. [8] predicted the future rate of soil erosion by modelling potential global soil erosion by employing shared socioeconomic pathway and representative concentrative pathway of IPCC climate scenarios (SSP-RCP). Furthermore, Dube et al. [146] have conducted an assessment on linear erosion features of rills and gullies erosion at a global scale. This study provided erosion modelling and spatial assessment of land susceptibility to concentrated flow erosion for the restoration of ecosystems. This review found that the capability of geo-informatics techniques could be utilized as a novel approach due to its vast application of potential and promising characteristics.

Spatial and Temporal Detection and Predictions

Implementation of sustainable landscape management policies and strategies depend on the basis of the spatial and temporal distribution of soil erosion hazard levels and risk assessment. The spatiotemporal pattern of soil erosion hazard has been studied and predicted by several researchers [142,147,148]. Nampak et al. [142] employed remote sensing technology to predict land-use change and its impact on soil erosion. They predicted land-use changes and soil erosion in the Cameron Highlands of Malaysia by 2025. Tehrany et al. [149] explored soil erosion hazard susceptibility mapping using evidential belief function and the frequency ratio by using nine conditioning factors based on A2 climate scenario for the present situation and predictions for 2100. However, it is still a challenge to analyze, understand and predict the situation with dynamic factors such as rainfall, land-use and land cover with the present climate variation.

The advances of geo-informatics and erosion models help to develop systematic and integrated approaches in soil erosion hazard and risk evaluation. Due to the complex nature of the soil erosion hazard process, several integrated approaches were applied. Some of these studies focused on the development of a set of criteria and indexes which can be spatially represented as information layers to quantitative and qualitative assessment [14,46]. In many recent research studies, soil erosion hazard models were combined with several statistical approaches and algorithms in a geospatial environment to quantify the assessment [150,151]. Such as expert decision tree and artificial neural-network evaluation methods [74], geo-statistical multivariate approaches [152], sensitivity analysis approaches [153], soft computing method [154] and analytical risk evaluation methods [155,156]. These models can be categorized into four types—expert knowledge-based models, data-driven models, machine learning model and hybrid method. This review focuses on geo-informatics involvement in one of the major types of soil erosion hazard, that is, gully erosion in detail.

Gully Erosion Mapping

Gully erosion is one of the important indicators in soil erosion hazards and it has been a great threat to agriculture by reducing soil fertility all over the world especially in arid and semi-arid regions in tropical, sub-tropical and temperate countries [157]. Gully erosion has become more common due to the impact of the climate change effect [6]. The high intense rainfall events in a bare landscape create gully incisions [32,158]. Furthermore, they discharge a high amount of sediment into water sources [157,159]. The studies conducted in Australia have identified land-use change such as vegetation clearance, animal grazing and alternating periods of extreme rainfall events and drought events, heavily induced gully erosion [34,41,160]. Li et al. [161] have also claimed that the reduction of vegetation cover greatly contributes to gully development.

Remote sensing and GIS-based models have been applied to identify spatial and temporal distribution, investigate susceptibility to gully erosion and mapping the risk classes in order to minimize soil erosion [162]. Image analysis techniques in satellite remote sensing such as object-based analysis have been incorporated into detecting and mapping gullies in numerous studies. In addition, several scientists have adapted advanced statistical, knowledge-based and machine learning models for gully erosion assessment. Most of these research studies attempt to find out gully susceptibility using soil, terrain, climatic and land use aspects with geo-informatics technology for the landscape evaluations. Several recent studies with adapted geo-informatics technology for gully erosion mapping are summarized in Table 4 below.

As previously mentioned, a sufficient level of research attention was given in the literature for gully erosion susceptibility mapping. However, soil erosion susceptibility mapping has received less attention compared to other natural hazards assessment in the literature [149]. According to Tehrany et al. [127], a variety of statistical and advanced methods such as evidential belief function (EBF), weights-of-evidence (WoE) and adaptive neuro-fuzzy inference system have been applied and tested in the field situations of flooding and landslides but not in soil erosion hazard modelling. In fact, few new research attempts can find out from recent studies on soil erosion susceptibility mapping using weights-of-evidence (WoE) and evidential belief function (EBF) models [62]. However, continuous attention is required to find potential best solutions and strategies to prevent these hazard situations in order to maintain a sustainable landscape and farming systems.

Table 4. Gully erosion assessment and mapping models.

Model Type	Country	Attributes	Techniques	Reference
Knowledge-based model	Iran	Elevation, slope degree, slope–length (LS), slope aspect, plan curvature, lithology, distance from the river, drainage density, distance from the road, use/land cover, topography wetness index (TWI), stream power index (SPI), land normalized difference vegetation index (NDVI),	Analytic Hierarchy Process (AHP)	[150]
Statistical Models	Iran	Soil texture, lithology, altitude, slope angle, slope aspect, plan curvature, land use, topographic wetness index (TWI), drainage density and distance from rivers	Certainty Factor (CF), a bivariate statistical model;	[163]
Machine learning model	India	Soil type, altitude, Slope gradient, slope aspect, plan curvature, land use, slope length (LS), drainage density, topographical wetness index (TWI), distance from the river and road, distance from the lineament,	Flexible discriminant analysis (FDA), Random forest (RF), Multivariate additive regression splines (Jin et al.) and Support Vector Machine (SVM).	[157]
Machine learning model	Iran	Elevation, slope degree, slope aspect, plan curvature, profile curvature, catchment area, stream power index, topographic position index, topographic wetness index, land use and normalized difference vegetation index	Generalized linear model, boosted regression tree (BRT), multivariate adaptive regression spline and artificial neural network (ANN).	[164]
Machine learning model	Australia	Digital elevation model, Annual precipitation, Geology, Temperature, land-use, soil characteristics, distance to the river and so on	Random forest	[165]
Knowledge-based model	China	Topographic factors, Vegetation cover and land use	Remote sensing techniques with visual interpretations	[161]
Knowledge-based model	Morocco	Slop, Specific catchment area, Flow direction, stream power index, Sediment transport capacity index, NDVI	Object-based image analysis	[166]
Hybrid method	Iran	Elevation, slope, soil type, lithology, plan curvature, stream power index (SPI), topographic wetness index (TWI), distance to road, distance to stream, drainage density, land use/land cover and rainfall	Weighted regression (GWR), Certainty factor (CF) and Random forest (RF)	[167]

4. Management Strategies

The farming systems are vulnerable to the impacts of climate variability and extreme events [7]. Climate variation also causes several adverse impacts on infiltration, runoff and soil erosion, consequently reduction of crop biomass and land-use change in farming systems [38]. Therefore, reliable measures and investment in climate and environment monitoring actions to address these issues effectively are required. Soil erosion and runoff assessment along with predictions are essential to implement conservation measures as well as rehabilitation planning for improving sustainable productivity on the long-term basis [168,169]. Pradhan and Lee [170] described soil erosion susceptibility and hazard assessment with prediction models that contribute to a significant reduction of damages. Hence, a better understanding of soil erosion rates and the effects of climate variables are important for the revision of land-use policies and better soil and water conservation measures in farming systems. Persichillo et al. [171] have emphasized the maintenance of man-made mechanical structures are very important to prevent mass movement. In addition, more efforts are needed to develop or improve effective erosion control techniques and strategies for soil erosion-prone areas using biological conservation methods such as live vegetation cover.

The soil erosion hazard maps are important to identify erosion-prone areas with its magnitude for detection of the vulnerability [14]. Rahman et al. [11] observed that soil erosion hazard and risk assessment are key factors in risk management. Although a significant number of techniques are available, Ashournejad et al. [172] have noted geo-informatics technology such as aerial and satellite images, GIS techniques, satellite and ground-based geodetic techniques, a global positioning system (GPS) provide a better understanding of risk reduction. In addition, soil erosion hazard maps provide a foundation for a further analytical tool for gully erosion, landslide susceptibility and risk identification [149]. Hence, continuous monitoring and evaluation of mass movement using geo-informatics technology are important for risk reduction and damage prevention.

Accurate mapping of susceptibility to erosion hazard is crucial to avoid economic losses and life losses. To improve the land resources by hazard mitigation in regional development planning; conservationists and policy-makers must understand how landforms, soil types, farming practices and interaction with rainfall and water runoff on soil erosion process. Vrieling [97] highlighted the importance of the validation process of data and maps. Ganasri and Ramesh [50] indicated that validation could be done with ground-level data. However, when ground-level data and previous research data were absent, it was very difficult. It is vital to compile and analyze valuable metadata before they are lost for future generations [6]. Hence, large-scale data collection (data mining) of published data on soil erosion rates, causative factors and sediment yield can be utilized for future benefits.

Few studies have been conducted using different methods and criteria to develop indices and metrics to evaluate the sustainability of the agricultural landscape. Metrics enable a quantitative and objective analysis of the different types of agriculture landscape [173]. A quantitative model was proposed on land planning and management scenario to identify the sustainability of olive farms in Andalusia, Spain [174]. This study used different conditions of soil erosion and management practices as criteria for modelling of abandonment, production and economic benefits of Olive farms. In addition, multicriteria evaluation method was used by several other researchers to identify land capability and suitability for agricultural activities by utilizing the physical characteristics such as soil depth, soil texture, soil drainage, erosion hazard, land-use, altitude, slope and slope direction [175,176]. Montgomery et al. [177] have utilized the GIS-based Logic Scoring of Preference (LSP) method as an effective tool for decision-making on agricultural land capability and land suitability assessment in Colorado, USA. It was an improved multicriteria evaluation method which comprises social, economic and physical characteristics as evaluation criteria: soil, topographic, climatic, economic, land-use and accessibility attributes for the analysis. Furthermore, Gray et al. [178] have developed a new matrix scheme to guide sustainable land management in New South Wales, Australia. This scheme was used to identify the potential impact of various land degradation hazards and to promote sustainable land management practices across the region. Hence, the development of sustainable landscape indices and matrix with a proper monitoring system will guide scientific land management under the context of climate variation to minimize its adverse impacts on land resources. Therefore, landscape indices and matrix can be developed using geo-informatics technology to evaluate the land capability and identify sustainable land-uses. Moreover, it is important to identify ecologically viable and economically sound farming systems with future climate scenarios for sustainability. Therefore, this review provides important directions on geo-informatics application for agricultural land vulnerability assessment and developing models for future climatic variation that help to formulate management strategies for climate-related risks reduction in farming systems. Furthermore, this work provides significant insights to assess ecological viable and economically sound farming systems against soil erosion hazards for future implications.

5. Challenges, Innovations and Future Directions

The complexity of morphological and other parameters in the larger land area is a more significant challenge for soil erosion assessment and risk evaluation. Soil erosion assessment models as such RUSLE/USLE have some drawbacks when predicting sediment pathways from hill slopes to water bodies and gully erosion assessment [179]. When combined with geo-informatics techniques: geospatial modelling and image fusion techniques can obtain successful research outcomes from soil erosion assessment. Hence, it has been suggested that remote sensing-based soil erosion assessment is more innovative and practicable for larger landscape [57]. Although high-resolution commercial remote sensing data have more potential, freely available Landsat archive data have been commonly used for remote sensing-based soil erosion modelling studies. Freely available Sentinel satellite data from the European Space Agency also has a great potential for future soil erosion studies with its high temporal resolution and SAR sensor. The SAR (microwave/radar) sensor of Sentinel satellite avoids misclassification due to cloud and haze. SAR is an 'active' remote sensing method and can be collected real-time data in the day and night under all weather conditions [180]. For example, multi-temporal X-band SAR (TerraSAR-X) [181,182] and GF-3 [183] have been used for soil moisture retrieval studies. Sepuru and Dube [57] suggested that Sentinel data have a high potential for temporal scale soil erosion assessment with 10 m resolution and 5-day repeat coverage. Similarly, the short revisit time satellites data of the Canadian RADARSAT, the Japanese ALOS, PALSAR-2 and the Himawari-8 have a great potential for temporal analysis, which can be facilitated to detect potential soil erosion hazards: emerging gullies in farmlands and susceptibility for landslide in the larger extent of a landscape. Moreover, detail and extensive monitoring and quantification of soil erosion using the above satellite data will help to prevent and control soil erosion in a sustainable manner. The multi–temporal topographic data provide better opportunity to detect geomorphological changes such as landslide movements, gully erosion and detection of faults in earth surface [113]. Furthermore, cloud-based geospatial data platforms such as the Google Earth engine and Land Viewer can support for the time series data analysis.

In addition, many studies indicate rainfall erosivity highly correlated with soil erosion and soil erosion hazards [36]. Moreover, spatially adjoining soil moisture data (SMAP) and radar/microwave base spatial rainfall data (PR (Precipitation Radar (Tropical Rainfall Measurement Mission), AMSR (Advanced Microwave Scanning Radiometer)) can be utilized as reliable data sources [112] for future research on rainfall intensity and variation and potential soil erosion hazard in farming systems, spatial-temporal assessment and prediction of climate scenarios.

However, increasing the availability of satellite data is also challenging, as the processing period may also increase in data analysis. The capabilities of remote sensing-based and GIS software can be utilized for processing the satellite data. Artificial Intelligence GIS techniques (AIGIS) such as GIS incorporated with machine learning and deep learning techniques such as data mining software have an excellent opportunity for satellite data handling.

6. Conclusions

Soil erosion has generated several issues in agriculture landscape and farming systems worldwide. As a result, crop production losses and economic losses are countless. This review provides evidence from literature, that soil erosion has been a great threat of land productivity: in terms of damages to the soil physical, chemical and biological structure, resulting in erosion hazard which leads for low agricultural productivity, economic damages and threats to human lives.

The review emphasizes that more research needs to be done on the spatial and temporal pattern of soil erosion with present rainfall variation, need of developing new techniques and strategies to landscape evaluation to improve the environmental condition sustainably. It further reveals less research attention on the spatial and temporal pattern of soil erosion along with rainfall characteristics such as rainfall amount, rainfall intensity, rainfall depth, erosivity and the number of rainy days with present climate variation. The relationships between rainfall variation and potential soil erosion hazards in different climatic regions are still far from clear in the literature.

Geo-informatics technology provides a platform with advanced capabilities and potentials of real-time hazard detection with a spatiotemporal distribution and soil erosion hazard predictions. Thus, geo-informatics can be applied for continuous monitoring and evaluation of soil erosion hazard to risk reduction and prevent the damage in farming systems. In addition, geo-informatics provides satisfactory real-time data sources with efficient data mining algorithms for effective analysis to solve real-time issues. Outcomes of these analyses can be used to estimate erosion rates, the effects of climate variation and could help to develop new indices and matrix for sustainable management of farming systems.

Finally, this review provides several implications for academicians, researchers and policy planners. Soil erosion rates and soil erosion hazard susceptibility maps provide information for vulnerable areas and its determinants, which will be useful to develop new models and applications in future research for predictions and sustainable farming systems development. A combination of multi-temporal data: commonly used optical satellite data, microwave short revisit satellite data and UAV data have enormous potential to predict soil erosion hazard in farming systems against future climate scenarios. Policy planners could utilize the outcomes of soil erosion hazard assessment to guide appropriate actions such as measures of soil and water conservation and recommendations for sustainable landscape development and natural resource management in the future.

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