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Abstract

Soil erosion is a significant problem for most of the agroecosystems worldwide, as it is one of the primary causes of soil degradation caused by a loss of the topsoil layer and soil organic matter, which are essential for plant development. Soil erosion models, typically developed for large-scale, are used to estimate soil loss and its impact on crop production. Numerous experimental and modeling techniques have been developed using approaches ranging from analytical to empirical techniques to gain a better understanding of runoff and soil erosion processes and their potential outcomes (organic carbon and nitrogen losses, soil depth reduction, etc.). While the processes driving soil erosion are well understood, the distributed and small-scale nature of erosion processes makes it difficult to quantify the severity of the erosion problem at the field scale under spatially heterogeneous soil and terrain conditions. A thorough analysis of identifying and categorizing the main causes of soil erosion at the field scale based on observations with a high spatial resolution for quantitatively assessing the spatial and temporal variability of soil erosion patterns is of great importance. This thesis presents a systematic analysis of (i) the limitations and applicability of existing modeling approaches (ii) within-field variability of the effects of the interaction between soil characteristics, topography, rainfall intensity, and soil cover on soil erosion and surface runoff, carbon and nitrogen losses (iii) insights into the uncertainties involved in the simulation of sub-field scale runoff and soil erosion processes due to the model structure and parameter estimation. Three specific studies were designed to increase understanding of these issues:

(1) Soil erosion models based on their representation of the soil erosion process were investigated. In total 51 different models were evaluated based on their representation of the processes of soil erosion by water. Secondly, their suitability for assessing soil erosion for more complex field designs, such as patch cropping, strip cropping and agroforestry (alley-cropping systems), and other land management practices were considered. The results showed that a particular shortcoming of most of the existing field scale models is their one-dimensional nature. Moreover, only a few models are suitable for dynamic soil erosion assessments at the field-scale. To date, there are no field-scale dynamic models available considering complex agricultural systems for the simulation of soil erosion.

(2) A field-scale study in Großmutz (Brandenburg), where an individual field with about 6 ha covers several landscape elements and is therefore characterized by a strong soil heterogeneity, was conducted to systematically analyze the influence of heterogeneous field conditions and

rainfall intensities along with their complex interactions on sediment losses and surface runoff. The interactive effects of these factors and their combinations were visualized from the analysis of signal-to-noise (S/N) responses. Results indicated that interactions between the selected factors and soil erosion processes exist and multiple linear regression models were developed to predict sediment yields, runoff, carbon, and nitrogen losses at the sub-field scale. Results revealed that (i) Rainfall intensity with 40.6% showed the highest contribution to sediment yield followed by Slope steepness (23.8%), Vegetation cover (17.74%), Silt and organic matter content (14.77%), and Depth to loamy layer (3.17%), indicating a strong rainfall intensity and erosion relationship; (ii) the combination of levels of factors generating highest sediment yield was determined; (iii) A simple multiple linear regression model developed for predicting local sediment yield showed the highest agreement with field observations (R2=82.5%).

(3) Finally, the accuracy of soil erosion models with different model structures in the same field with heterogeneous soil and terrain conditions was tested. For this purpose, two widely used methods (Freebairn and Rose) to represent soil erosion and coupled them with a process-based crop model within the SIMPLACE framework. Spatiotemporal measurements of the soil and crop dynamics were taken in a heterogeneous field to calibrate and evaluate a range of model solutions. The accuracy of these model solutions coupling different modeling approaches was compared to a statistical model developed for the same field. The results indicated that the simulations of water erosion with the dynamic Freebairn and Rose approaches were influenced by the performance of the runoff and crop growth sub-models. However, a pronounced difference was found between modeled and measured soil erosion when these predictions were made with an uncalibrated runoff model. Hence, our results highlighted that large uncertainties in soil erosion modeling were associated with improper performance of the runoff model.

After an analysis and synthesis of the results of all three studies in this thesis, it was concluded that an improved understanding of complex interactions among multiple factors influencing the soil erosion process is an important area of research for future soil erosion studies as well as new model developments since this understanding of the connection between small-scale field conditions in the agricultural landscape is as important as understanding absolute sediment yield. Since plot-based studies for data collection and for implementing modeling techniques in complex agricultural landscapes are difficult and labor intensive, it is important to adequately design further plot-scale studies to maximize the usefulness of the collected data for upscaling modeling approaches to larger scales.

Zusammenfassung

Bodenerosion stellt für die meisten Agrarökosysteme weltweit ein erhebliches Problem dar, da sie eine der Hauptursachen für die Verschlechterung der Bodenqualität ist: Bodenerosion kann dazu führen, dass die oberste Bodenschicht und die organische Bodensubstanz, die für die Entwicklung der Pflanzen unerlässlich sind, abgetragen werden und verloren gehen. Bodenerosionsmodelle, die in der Regel für den großflächigen Einsatz entwickelt werden, dienen der Abschätzung des Bodenverlusts und seiner Auswirkungen auf die pflanzliche Erzeugung. Es wurden zahlreiche Versuchs- und Modellierungsmethoden entwickelt, die von analytischen bis hin zu empirischen Verfahren reichen, um ein besseres Verständnis der Abfluss- und Bodenerosionsprozesse und ihrer potenziellen Folgen (Verluste an organischem Kohlenstoff und Stickstoff, Verringerung der Bodentiefe usw.) zu erlangen. Die Prozesse, die zur Bodenerosion führen, sind zwar gut erforscht, jedoch können kleinräumige heterogene Boden- und Geländebedingungen die Quantifizierung des Ausmaßes des Erosionsproblems auf der Feldskala erschweren. Eine gründliche Analyse zur Identifizierung und Kategorisierung der Hauptursachen von Bodenerosion auf Feldskala, basierend auf der Grundlage von Beobachtungen mit hoher räumlichen Auflösung, ist, zur quantitativen Bewertung der räumlichen und zeitlichen Variabilität von Bodenerosionsmuster, von großer Bedeutung. Die vorliegende Arbeit enthält eine systematische Analyse (i) der Grenzen und der Anwendbarkeit bestehender Modellierungsansätze, (ii) der Variabilität von Auswirkungen und Wechselwirkung zwischen Bodeneigenschaften, Topographie, Niederschlagsintensität und Bodenbedeckung auf Bodenerosion und Oberflächenabfluss sowie Kohlenstoff- und Stickstoffverluste innerhalb eines Feldes und (iii) der Unsicherheiten bei der Simulation von Abfluss- und Bodenerosionsprozessen auf Teilschlägen, die auf die Modellstruktur und die Parameterschätzung zurückzuführen sind. Drei spezifische Studien wurden durchgeführt, um das Verständnis für diese Fragen zu verbessern:

(1) Es wurden Bodenerosionsmodelle auf der Grundlage ihrer Darstellung des Bodenerosionsprozesses untersucht. Insgesamt wurden 51 verschiedene Modelle auf der Grundlage ihrer Darstellung der Prozesse der Bodenerosion durch Wasser bewertet. Zweitens wurde ihre Eignung für die Bewertung der Bodenerosion bei komplexeren Feldgestaltungen wie Patch-Cropping, Strip-Cropping und Agroforstwirtschaft (Alley-Cropping-Systeme) sowie bei anderen Landbewirtschaftungspraktiken untersucht. Die Ergebnisse zeigten, dass ein besonderes Manko der meisten bestehenden Modelle im Feldmaßstab ihre Eindimensionalität ist. Außerdem

eignen sich nur wenige Modelle für die dynamische Bewertung der Bodenerosion auf der Feldskala. Bislang gibt es keine dynamischen Modelle im Feldmaßstab, die in der Lage wären Bodenerosion in komplexen Anbausystemen zu simulieren.

(2) Um den Einfluss heterogener Feldbedingungen und Niederschlagsintensitäten sowie deren komplexe Wechselwirkungen auf Sedimentverluste und Oberflächenabfluss systematisch zu analysieren, wurde eine Feldstudie in Großmutz (Brandenburg) durchgeführt. Dabei wurde ein einzelnes Feld mit etwa 6 ha ausgewählt, das mehrere Landschaftselemente umfasst und daher durch eine starke Bodenheterogenität gekennzeichnet ist. Die interaktiven Auswirkungen dieser Faktoren und ihrer Kombinationen wurden anhand einer signal-to-noise (S/N) Analyse ausgewertet. Die Ergebnisse zeigten, dass es Wechselwirkungen zwischen den ausgewählten Faktoren und den Bodenerosionsprozessen gibt. Auf dieser Basis wurden multiple lineare Regressionsmodelle entwickelt, um Sedimenterträge, Abfluss, Kohlenstoff- und Stickstoffverluste auf der Teilschlagebene vorherzusagen. Die Ergebnisse zeigten, dass (i) die Niederschlagsintensität mit 40,6 % den höchsten Beitrag zum Sedimentertrag leistete, gefolgt von der Hangneigung (23,8 %), der Vegetationsbedeckung (17,74 %), dem Gehalt an Schluff und organischer Substanz (14,77 %) und der Tiefe der lehmigen Schicht (3. 17%), was auf eine starke Beziehung zwischen Niederschlagsintensität und Erosion hinweist; (ii) die Kombination von Faktoren, die den höchsten Sedimentertrag erzeugen, wurde bestimmt; (iii) ein einfaches multiples lineares Regressionsmodell, das zur Vorhersage des lokalen Sedimentertrags entwickelt wurde, zeigte die höchste Übereinstimmung mit den Feldbeobachtungen (R2=82,5%).

(3) Schließlich wurde die Genauigkeit von Bodenerosionsmodellen mit unterschiedlichen Modellstrukturen auf dem oben beschriebenen Feld mit heterogenen Boden- und Geländebedingungen getestet. Zu diesem Zweck wurden zwei weit verbreitete Ansätze (Freebairn und Rose) zur Simulation der Bodenerosion verwendet und mit einem prozessbasierten Nutzpflanzenmodell im Rahmen von SIMPLACE gekoppelt. Räumliche und zeitliche Boden- und Pflanzendynamik wurden in einem heterogenen Feld gemessen, um eine Reihe von Modelllösungen zu kalibrieren und zu bewerten. Die Genauigkeit dieser Modelllösungen, die verschiedene Modellierungsansätze verbinden, wurde mit einem statistischen Modell verglichen, das für dasselbe Feld entwickelt wurde. Die Ergebnisse zeigten, dass die Simulationen der Wassererosion mit den dynamischen Ansätzen von Freebairn und Rose am stärksten von der Güte der Teilmodelle für Abfluss und Pflanzenwachstum beeinflusst wurden. Es wurde ein deutlicher

Unterschied zwischen der modellierten und der gemessenen Bodenerosion festgestellt, wenn die Simulationen mit einem nicht kalibrierten Abflussmodell gemacht wurden. Unsere Ergebnisse machen deutlich, dass große Unsicherheiten bei der Modellierung der Bodenerosion mit einer unzureichenden Leistung des Abflussmodells verbunden sind.

Nach einer Analyse und Synthese der Ergebnisse aller drei Studien in dieser Arbeit kamen wir zu dem Schluss, dass ein verbessertes Verständnis der komplexen Wechselwirkungen zwischen mehreren Faktoren, die den Bodenerosionsprozess beeinflussen, ein wichtiger Forschungsbereich für künftige Bodenerosionsstudien sowie für die Entwicklung neuer Modelle ist, da dieses Verständnis der Zusammenhänge zwischen kleinräumigen Feldbedingungen in der Agrarlandschaft ebenso wichtig ist wie das Verständnis des absoluten Sedimentertrags. Da parzellenbasierte Studien zur Datenerhebung und zur Umsetzung von Modellierungstechniken in komplexen Agrarlandschaften schwierig und arbeitsintensiv sind, ist es wichtig, weitere parzellenbasierte Studien angemessen zu konzipieren, um den Nutzen der gesammelten Daten für das Upscaling von Modellierungsansätzen auf größere Maßstäbe zu maximieren.

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Chapter 1

General Introduction

1. General introduction

Sustainable agriculture production depends on the conventional and potential use of available soil and water resources (Lichtfouse et al., 2009). Soil erosion is one of the main causes where the soil is subjected to degradation as a result of detachment and displacement of topsoil particles. Soil erosion is a complex phenomenon as it is governed by various natural processes resulting in a decrease in soil fertility, reduction in rooting depth, and consequently reduced crop yield (Pimentel, 2006). Each year, soil erosion causes 75 billion tons of soil loss annually largely from agricultural land, and about 20 million hectares of land is already lost in this process (Pimentel et al., 1995). Agricultural practices account for 75% of global soil erosion, affecting 80% of the world's cultivated soils (Pimentel, 2006). Water erosion is responsible for the biggest share of soil loss in Central European agricultural ecosystems (Panagos et al., 2015). Studies in Lower Saxony, Germany show the highest annual loss on a single field was 53.07 t ha^{-1} y^{-1} (Steinhoff-Knopp and Burkhard, 2018).

Effective modeling of water erosion can provide important information about soil erosion patterns and trends and additionally allows scenario analysis concerning different climate conditions and field characteristics (Krysanova et al., 2007). However, estimating soil erosion is challenging as it involves many processes that vary within space and time (Driessen, 1986). These challenges in soil erosion modeling are due to the variability and complexity of natural and human intervention in the soil erosion process. Soil erosion in agriculture systems is a function of soil characteristics (soil texture, soil moisture, and infiltration), land use (crop type), topography (slope steepness), and climate (rainfall intensity). Adding to this the variant nature of these functions; within single field agriculture systems can have a vastly variant rate of soil erosion and sediment yield. Due to this stochastic nature of field environmental processes, soil erosion models should be able to involve multiple natural and field conditions with their complex interactions and integrated with dynamic crop growth and soil-water balance. Moreover, plot-based observations need to be combined with erosion models to ensure acceptable model performance and for validating model outcomes.

1.1. State of the art in modeling soil erosion processes

In an effort to simulate the impacts of soil erosion on agricultural land, soil erosion models have been developed to improve our understanding of how different natural processes and field management practices can influence the soil erosion process. Many different algorithms and relations have been proposed to define and predict soil erosion by water and associated sediment yield, but varying significantly in their objectives, time scale, and in their conceptual basis as well. These models are generally used to study soil loss in different environmental conditions (Alewell et al., 2019; Parsons et al., 2004; Renard et al., 1991) and have typically been developed for larger-scale applications, such as basin or watershed scales under specific field characteristics and climatic conditions (Li et al., 2020). At field or plot scale, some soil erosion models by water were also developed (Ahmadi et al., 2020; Dilla et al., 2020; Eisazadeh et al., 2018, 2012), but the use of such models in conditions of high in-field heterogeneity is challenging. These uncertainties mainly arise from complex processes that can strongly vary within single fields, particularly in undulated areas (Cerdan et al., 2010).

The ability of soil erosion models to consider dynamic interactions among vegetation cover, soil moisture conditions, field topography, and spatial heterogeneity of soil physical and hydrological properties makes them a strong tool to simulate dynamic soil erosion predictions and also to assess the impact of different field and environmental conditions on soil loss. The application of soil erosion models is very promising in understanding and quantitatively assessing the spatial and temporal variability of soil erosion patterns at a small scale when integrated with other dynamic agroecosystem models. There are especially two areas that require critical reflection in this respect.

Firstly, individual hydro-geomorphological processes and vegetation dynamics affect the soil erosion process differently depending on the scale (Aga et al., 2020; M. A. Nearing et al., 2011; Panagos et al., 2015) under specific field conditions. Thus, when applying soil erosion models under highly spatial heterogeneous field conditions, uncertainties about parameters values selection have to be handled properly in the calibration and validation of models to produce reliable dynamic results for small scale assessments of soil loss and runoff.

Secondly, the application of small-scale soil erosion models requires detailed information about soil, weather, crop, and field management data. Due to the high spatial and temporal variation of aforementioned parameters within the field, challenges arise in adequate input data of observing multiple factors and their complex interactions to apply the model at a small scale need to be addressed. It is difficult to describe soil erosion over spatial and temporal scales due to limitations in the field measurements for each part of the study area. In this regard, it is essential to develop experiment strategies under prevailing field and natural environmental conditions to consider the multiple factors and their complex interactions that can drive fine-scale spatial soil erosion processes.

Statistical models have been employed to investigate soil erosion by water at different temporal and spatial scales (Borrelli et al., 2021). Although easy to implement, these models generally present high predictive skills only for the boundary conditions for what these models were developed, being difficult to generalize or understand sub-processes of the system. On the other hand, the mechanistic models are aimed to provide process-based explanations of the soil erosion process caused by multiple factors and their interactions.

Over the last three decades, different empirical, physical, and conceptual models have been developed representing the soil erosion process by water and sediment transportation in overland flow. Their differences in the outputs and the uncertainties in model predictions have been the subject of several reviews. In the following years, an increasing number of research groups began to utilize different soil erosion models as dynamic assessment tools (Cabelguenne et al., 1995; Masere and Worth, 2015), especially (but not only) in the context of dynamic field conditions (White et al., 2011). Temporally dynamic erosion estimations have been conducted with some landscape models such as SWIM (Krysanova et al., 2005), IQQM (Simons et al., 1996), TOPMODEL (Beven et al., 1984), and LASCAM (Zammit et al., 2003). Such dynamic models tend to predict accurately sediment transport and deposition but their application is normally limited due to a lack of input information, a poor representation of vegetation dynamics as well as uncertainties related to the parameters involved. Most often, these models require detailed input data for calibration and outstanding computing systems, when applied at larger scales. Consequently, it's necessary to establish simulation protocols and to suggest techniques to consider temporally and spatially varying field conditions such as soil heterogeneity, crop cover dynamics, and rainfall event characteristics within a single field.

Despite the ability to investigate, and predict the dynamic nature of soil erosion processes, most of these models do not provide reliable erosion prediction over spatially and temporally highly heterogeneous soil cover and soil physical properties at the field scale. Nevertheless, a few studies found in the literature where attempts were made to investigate the impact of multiple environmental and in-field factors to predict sediment yield and runoff, are investigated, including, in some cases, carbon and nitrogen losses under natural conditions (Cakula et al., 2012; Meena et al., 2020; Wei et al., 2007). Most of these studies consider only a few factors (i.e., rainfall, soil cover, or slope) (Guidry et al., 2006; Sepaskhah and Bazrafshan-Jahromi, 2006)to explain the erosion process. Studies investigating the uncertainties in field scale erosion model applications introduced by parameters (Brazier et al., 2000) and their complex interactions are almost an exception. Recent studies (Keller et al., 2021; Masere and Worth, 2015) have proven the effectiveness of dynamic soil erosion models when integrated into agroecosystem models (i.e., simulating soil-water dynamics and crop growth at high temporal and spatial resolution). The integrated model tends to simulate the dynamics of vegetation cover under specified field management schemes, runoff, and erosion processes such as APSIM or EPIC modeling frameworks.

In the present study, the terms spatial scale, resolution, and sediment yield will be consistently used. Accordingly, scale is used as a synonym for spatial extent and refers to the spatial dimension of the area where a phenomenon or a process occurs. The term resolution refers to the ratio between the area covered by observations and the total area considered by a study (extent). Finally, the sediment yield, during a specified period of time, represents the amount of sediment per unit area removed by flowing water.

1.2. General objective and research questions

The overarching goal of the current Ph.D. thesis is to methodically identify and address the uncertainties arising from the field scale application of soil erosion models under spatially heterogeneous field conditions. In response to the need for further understanding of the key components and uncertainties inherent to the dynamic modeling of soil erosion, this thesis aims to answer the following three questions.

Question 1 (Q1): What are the existing modeling approaches to assess soil erosion by water at the field scale with special emphasis on the heterogeneity of soils and crops?

Question 2 (Q2): What are the effects of field and environmental factors influencing water erosion at the plot scale?

Question 3 (Q3): What uncertainties are involved in the dynamic simulation of sub-field scale run-off and soil erosion processes due to the model structure?

Q1 mainly focuses on examining the different soil erosion modeling approaches for predicting soil losses. This includes reviewing their underlying concepts, data requirements, and sources of uncertainties involved. Q2 deals with identifying and categorizing the main causes of soil erosion at the field scale based on observations with a strategically designed experiment scheme, especially for quantitatively assessing the spatial and temporal variability of soil erosion patterns. Q3 provides insight into the capabilities of the integrated soil erosion model solution to simulate soil erosion under highly heterogeneous field conditions and to compare its performance with statistical models based on in-field observations.

1.3. Study setting

In order to answer Q1, a comprehensive review of soil erosion models was conducted. In this study, 51 models were selected based on their development criteria, model structure, model components, their application, simplicity of model calibration, and parameter specifications. Models were then categorized according to their capacity to explain the processes of soil erosion, data requirement, governing equations, spatial and temporal resolution, and application capabilities and limitations within heterogeneous field conditions.

The investigation of the impact of field and environment conditions on sediment yield and runoff dealing with Q2 was carried out on a spatially heterogeneous agricultural field site located in the Löwenberger (52° 56' 25.548" N, 13°7'57.648" E), Germany. The field which has been selected has a size of ~6.25ha and depicts a typical condition in the landscape of North East Germany. This region is intensively used as cropland and is characterized by soils formed from the glacial till of the last glacial period and later modified by fluvial and erosive processes, which created an enormous small-scale heterogeneity in the landscape. As the average field size is about 20 ha, the individual fields regularly cover several landscape elements, and, as a result, they are characterized by considerable soil heterogeneity. Thus, the advantage of the field is that it is representative of a large area and the results obtained can potentially be applied to the entire region. Based on the results, the influence of field characteristics on sediment yield was used to develop a local statistical model to estimate runoff volume, sediment yield, and carbon and nitrogen losses in various locations in the field.

Finally, an attempt was made to integrate selected conceptual erosion models and a process-based crop growth model to be applied to a large number of locations on the same field in order to answer Q3. This was performed using the Scientific Impact assessment and modeling platform (SIMPLACE). SIMPLACE is a platform for advanced crop and ecosystem management using modular software architecture to simulate complex environmental processes. The integrated model simulates the dynamics of vegetation cover under specified field management schemes, runoff, and erosion processes.

1.4. Structure of the thesis

The thesis comprises 5 chapters. **Chapter 1** is the general introduction, while chapters 2 to 4 deal with the three research questions in the order mentioned above. **Chapter 2** comprises a review of soil erosion modeling techniques. In this chapter, based on their representation of the soil erosion process, 51 models were screened and classified according to their application challenges for simulating field-scale erosion processes and their consideration of more complex cropping systems like alley cropping, patch cropping, and strip cropping. The findings provided the path to select adequate models for dynamic simulation of sediment yield at the field scale for an area with high spatial in-field variability. In **Chapter 3** the effects of the interaction between soil characteristics (soil organic matter (SOM), soil texture), topography (slope), rainfall intensity, and soil cover (field conditions) on soil erosion, surface runoff, carbon and nitrogen losses were investigated in the same field taking advantage of it high in-field variability. Different scenarios of rainfall events under different rainfall intensities were generated with a mobile rainfall simulator and combined with different levels of vegetation cover, slope inclination, and soil physical conditions. Based on the experimental results linear regression models were developed to predict sediment yield, runoff, carbon, and nitrogen losses. Additionally, in order to determine the regions of the field that are more susceptible to soil erosion, the regression equation for sediment yield was used to predict sediment yields within the field. **Chapter 4** provides the workflow for integrating the selected soil erosion models into the SIMPLACE framework to estimate sediment yield under heterogeneous field conditions considering dynamic soil-water fluxes with run-off and crop growth models as well as two different approaches to simulate sediment yield. Dynamic coupling of two soil erosion models was tested and simulated runoff and sediment yield were evaluated by comparing the estimations with observations at different temporal and spatial scales to assess the uncertainties due to model structure and data limitations. Moreover, the sensitivity of model calibration with respect to the soil physical and hydrological parameters has been analyzed to gain an insight into uncertainties resources due to model parameters. Finally, **Chapter 5** summarizes and discusses the main conclusions of this Ph.D. thesis. Research implications for future research and development attention are proposed and a set of recommendations are given related to the uncertainties in the application of soil erosion models at a small scale under heterogeneous field conditions.

1.5. Dissemination

Since this is a cumulative doctoral thesis, the central parts of the study (Chapters 2, 3, and 4) were submitted as scientific publications in peer-reviewed journals (MDPI/Science Citation Index (SCI) Web of Science List). Therefore, the international communities can have access to our research methods and results and apply the procedures developed in this thesis to future studies in similar regions. Details are listed in Table 1.1.

Table 1. 1. List of scientific publications in journals that are under MDPI /SCI Web of Science List

Chapter	SCI-Journal	Impact factor	Title
2	LAND	3.90	Modeling Approaches to Assess Soil Erosion by Water at the Field Scale with Special Emphasis on Heterogeneity of Soils and Crops
3	Science of the Total Environment	10.75	Using the Taguchi experimental design for assessing within-field variability of surface run-off and soil erosion risk
4	Environmental Modelling & Software	5.47	Comparison of predictive modeling approaches to estimate soil erosion under spatially heterogeneous field conditions (To be submitted)

Chapter 2

Modeling approaches to assess soil erosion by water at the field scale with special emphasis on heterogeneity of soils and crops

This chapter has been published as:

Raza, A., Ahrends, H., Habib-Ur-Rahman, M., Gaiser, T., 2021. Modeling approaches to assess soil erosion by water at the field scale with special emphasis on heterogeneity of soils and crops. Land. https://doi.org/10.3390/land10040422

1. Introduction

Soil erosion is a significant problem worldwide for most of the agro-ecosystems (Boardman and Poesen, 2006) because it is one of the primary causes of soil degradation as a result of detachment and loss of topsoil layer and soil organic matter, which are essential for plant development. Quantification of soil loss related to soil and crop management, climate, and soil conditions has, therefore, become a serious concern for water and soil conservation practitioners, as well as decision-makers concerned with food security and agricultural policies (Phuong et al., 2017). Soil erosion is the process of detachment and transportation of soil particles involving various erosive agents from the earth's surface. Categorized into wind and water erosion, water erosion is a much more complex process and leads to substantial loss of soil and sedimentation (Liu et al., 2018). Water erosion is mainly affected by rainfall/runoff intensity, vegetation cover, soil erodibility, topography, and land use management practices (Ahamefule et al., 2018).

Due to the rapid advancement in data computing techniques in the last three decades, there is a substantial enhancement in the analysis of soil erosion through the development of computer models (Merritt et al., 2003). However, these models strongly differ in terms of data requirement, application scales, and complexity, along with uncertainties in the individual factors of the respective models (Swarnkar et al., 2018). Water erosion modeling is about 60 years old, but has become a key factor in our understanding of the complexity of erosion processes and for predicting future scenarios. Yet, most of the models are still inadequate due to multiple sources of uncertainty (Favis-Mortlock and Mullan, 2011; Parsons et al., 2004).

Many different algorithms and relations have been proposed to define and predict soil erosion by water and associated sediment yield, varying noticeably in their objectives, time scale at the plot level, and in their conceptual basis as well. The choice of the most suitable model is a logical process affected by many factors including land use, the characteristics of the catchment being considered, and the data available (Ranzi et al., 2002). Physically based models, for example, mainly depend on the principal approach of mass and energy conservation to simulate runoff and sedimentation. In addition, physically based models are based on the concept of physics using transfer of momentum as a governing equation (Doe et al., 1999).

Remote Sensing and GIS have huge potential for analysis and mapping of parameters influencing soil erosion and degraded lands in quantitative and qualitative manners. However, the use of GIS for soil erosion modeling requires facilitations such as multiple data resources, data scaling, and increased complexity in data integration and algorithms. Climate, land use/land cover, topography, and slope data can be assessed using LIDAR or Satellite imageries and can be integrated with GIS for soil erosion, transport, and sedimentation modeling (El Jazouli et al., 2017; Haregeweyn and Yohannes, 2003; Patil et al., 2015; Renschler and Harbor, 2002).

There is an increasing interest in more complex field designs and crop diversification on the same field, e.g. alley cropping systems, as one of the most popular type of agroforestry, patch cropping, strip cropping, and uncultivated drylands, wherein rotational grazing livestock are moved to a part of the pasture, while the other portions rest, which can impact modeling outcomes. Consequently, a need for suitable soil erosion models that can handle and consider more complex field designs is raised.

The key objective of this study is, therefore, to categorize an extensive amount of available soil erosion models, review the underlying concepts, data requirements, and sources of uncertainty. We especially consider their suitability to simulate soil erosion at the sub-field scale and their application for more complex field designs. More specifically, we aim to

i. Provide a review of a large number of existing soil erosion models with respect to (a) the challenges for simulating field-scale erosion processes and (b) consideration of more complex cropping systems like alley cropping, patch cropping, and strip cropping, and based on these findings,
ii. Provide suggestions on a way forward for corresponding model improvements.

2. Materials and Methods

We performed a systematic model review with the reviewed soil erosion models being based on the outcome of a thorough literature screening, identification of suitable models, and model classification (Fig. 2.1). This review paper is structured in the following way. A brief explanation of soil erosion, transportation, and sedimentation principles is made in section 3.1. In this review, more than 60 models were reviewed and 51 models were retained in section 3.2. The shortlisted models are reviewed in terms of their objective, model structure, model components, as well as their application, ease of model calibration, and parameter requirements. Models are categorized in terms of their ability to explain the soil erosion processes, governing equations, their spatial and temporal resolution, their capabilities, and their limitations. These models have a wide range of applications from point scale to catchment scale. The focus of this review primarily considers models having abilities to simulate soil erosion process at the field scale and in complex cropping systems. The selected models are described in section 3.3. in which it is noted that many field scale models are implemented for catchment-scale soil erosion simulations. From a wider point of view, some of these models are described under their respective categories. In section 4, a discussion summarizes descriptions of models to sort out which model fits which conditions and problems identified and leads to clear guide-lines to select the appropriate model. This discussion is used to identify key points that would enhance the quality of the modeling output and the nature of additional components to enhance model capability in most environmental and management conditions. Section 5 provides a way forward on how to improve and extend existing models to simulate erosion processes at a small spatial scale in complex agriculture systems.

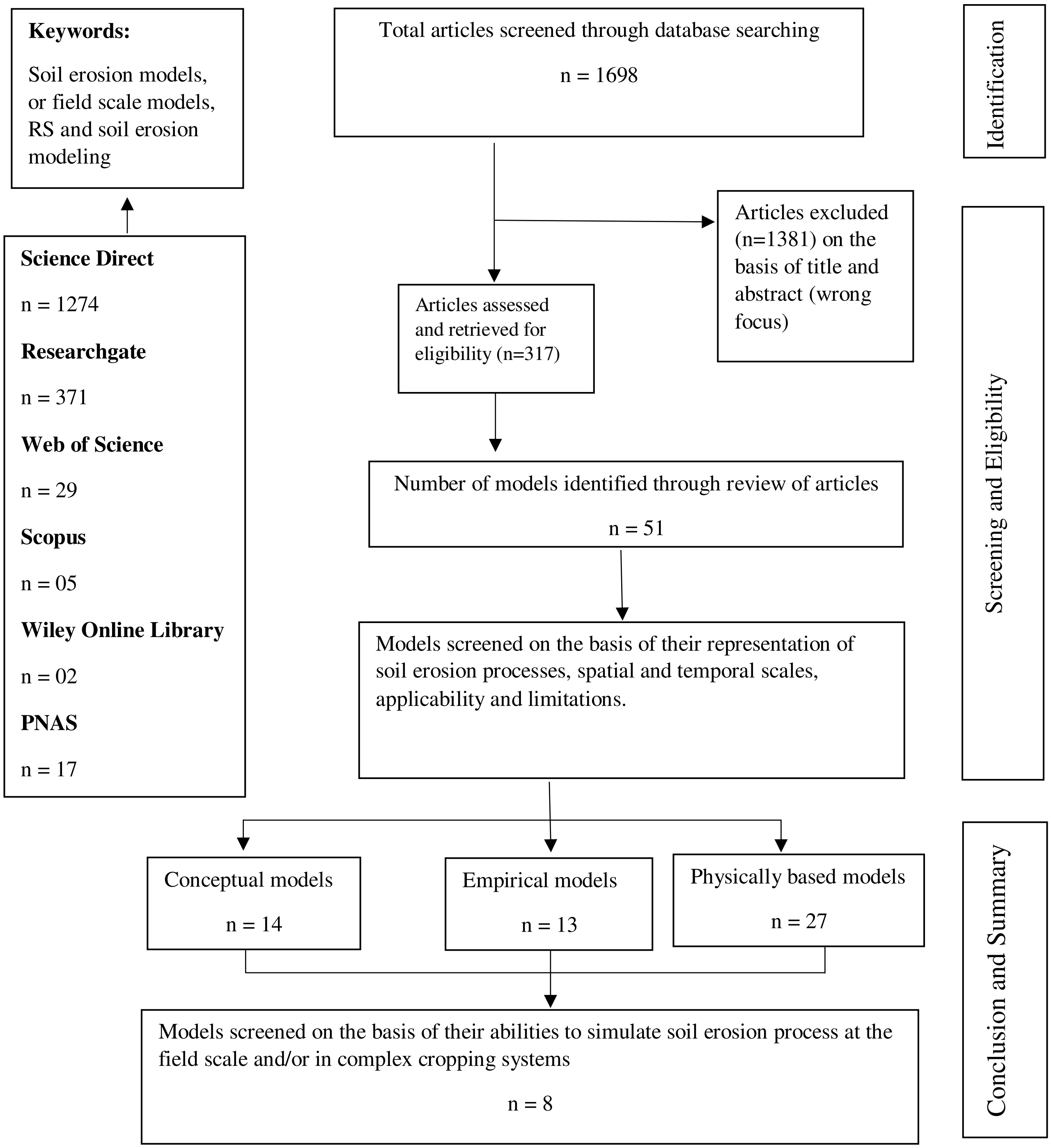

Fig. 2. 1: The literature study flow diagram

3. Results

3.1. Principles of Erosion Modeling

Sedimentological and hydrological processes involved in the modeling of soil erosion by water are explained mainly by two principles representing these processes (Table 2.1). Every erosion model can be considered as a unique permutation of these two principles (Favis-Mortlock et al., 2001).

Table 2. 1. Principles driving process representation in soil erosion models (modified after (Favis-Mortlock et al., 2001)

Principle	Summary
A model must represent all factors significantly contributing to the erosion process at the spatial, temporal, and locality levels for which the model is applied.	What to represent
A model may apply different weights to the individual processes or it may represent these processes directly, indirectly, or using a hybrid approach. (Favis-Mortlock et al., 2000).	How to represent

One of the critical aspects of the first principle (Table 2.1) is that every erosion model operates at different temporal and spatial scales (Kirkby et al., 1998a). Therefore, a plot-scale model must be able to represent a different combination of erosion processes as compared to those developed for the landscape (i.e., watershed or regional) scale (Table 2.2). Further, if simulating single events, the processes represented in the model may differ from those considered in models for long-term simulations or the weighting factors for each of the processes may be different. Similarly, erosion processes vary depending on the climatic conditions (i.e., humid, arid, etc.) and models developed for these specific regions must vary in terms of the number and type of erosion processes that are considered (Favis-Mortlock et al., 2000).

Table 2. 2. Spatial scale sizes for soil erosion modeling

Category	Spatial Scale	Size
Large scale	Basin	>500 km^2
	Catchment	50 – 500 km^2
	Watershed	1-50 km^2
Small scale	Field/hillslope	< 1km^2
	Plot	0.6-23 m^2

3.2. Soil Detachment and Sedimentation Assessment Model Approaches

A wide range of modeling approaches has been developed for simulating soil erosion and sedimentation over the last decades, differing in their representation of processes involved in soil erosion, the complexity of these processes, data requirements and output uncertainties, model calibration and use, and their temporal and spatial scale limitations. In general, the model selection depends on the intended application and characteristics of the landscape. Therefore, several factors must be considered before the model selection i.e., objective, data requirements, data availability, accuracy, validity, etc.

Each model has been designed for a specific spatial scale and purpose and thus is not appropriate and suitable for every application. Based on the complexity and the level of dynamic physical processes that are implemented, models can be categorized into three different groups, namely empirical, conceptual, and physically based models. Due to the increasing application of geospatial data, we further distinguish a fourth category: Remote Sensing and GIS-based modeling approaches. However, most of the models might be composed of different model categories. For example, the runoff-rainfall component of the USLE model (Monjezi et al., 2017) may be physically based but an empirical relationship has been developed for the estimation of soil erosion and sediment yield with little computational efforts. An example of so-called "hybrid models" is the Unit Stream Power-based Erosion Deposition and Automated Geospatial Watershed Assessment. The model structure is conceptual in nature considering the number of storages, while the configuration of these storages is determined through a statistical identification process for each catchment. The accuracy of these models is mainly dependent on the parameters selected and their primary implications. (Alewell et al., 2019) noted the primarily different nature of gross (modeled) vs net (measured) soil erosion.

3.2.1. Empirical Models

Empirical models are primarily based on observation data and the relationships be-tween different factors and soil erosion levels that were derived from these data sets. The computational and input data requirements for empirical models are lower than those required for conceptual or physically based models. Hence, empirical models are comparatively flexible, have a simple structure, are easily implemented, and useful in identifying the source of sedimentation generation as a first step. The most critical limitation of empirical models for soil erosion is their inadequate level of accuracy in analyzing large data sets which would require processing and analysis using special complex mathematical approaches (Eisazadeh et al., 2012).

Empirical models have proven to be robust since they are mathematically simple, but their application is limited to the extent of area for which they have been developed and calibrated for the fact that users will not get benefit from complex models if incomplete input data is available. They are often based on standard runoff plot schemes for uniform slopes (Parsons et al., 2004). At regional scales, with the identification of sediment settlement and delivery patterns, empirical models can be applied to predict average sedimentation, soil erosion rates, and surface runoff using the SCS curve number. If soil characteristics spatially do not vary and if spatially explicit meteorological data is not available, the application of robust empirical models can provide more reliable results as compared with more complex and dynamic models. However, empirical models work on the concept of stationarity, which makes them less powerful for predicting soil erosion for complex terrains characterized by heterogeneous soil characteristics and climatic conditions. Hence, empirical models are often applied when the availability of model input data is limited. Most of the empirical models do not provide information regarding sediment deposition and stream sedimentation generation, which restricts their application for simulating mass balances.

There are a few field-scale models such as EPM, TCRP, and SLEMSA which simulate soil detachment, transportation, and sedimentation using predominantly empirical approaches at field-scale (Table 2.3). The PSIAC model has the ability to estimate soil erosion and sedimentation at both field and catchment scales. These models are continuous simulation models that are useful for predicting the effects of field management practices and the effects of hydrological variations at daily time steps (Table 2.3). There are a few empirical models available to study the soil erosion processes under agroforestry systems such as WaNuLCAS, SCUAF, and HyPAR. Most of the models contain process-based sub-models to simulate the crop growth based on their vegetative and generative stages under specific field conditions (Probert et al., 1998) including all soil processes that may affect agricultural systems, such as C, P, N dynamics, and soil erosion (Probert et al., 1998). Models such as USLE, MUSLE, RUSLE, and MOSES have long-term simulation capabilities at both hillslope and catchment scale. Models are distinguished on the basis of spatial and temporal scale as de-tailed in Table 2.3.

Table 2. 3. Empirical soil erosion models

Sr. No.	Model	Description	Developer /year*	Scale		Input		Governing Equations	Model Capabilities	Model Limitations	Overland Sedimentation			Channel Sedimentation Generation	Source
				Temporal	Spatial	Demand	Variables				G*	T*	D*		
1	USLE	Universal Soil Loss Equation	(H.Wischmeier and Smith, 1949)	Annual	Catchment/ Hillslope	High	Climate data, topography, Land use/Land cover, field management practices, crop management factor	Universal Soil Loss Equation	Erosion	Does not quantify the events that are likely to result in large-scale erosion	No	Yes	No	No	(Albaladejo Montoro and Stocking, 1989)
2	MUSLE	Modified Universal Soil Loss Equation	(J. R. Williams and H. D. Berndt, 1977)	Annual	Catchment/ Hillslope	High	Volume flow rate, peak flow rate, erosion control practices, crop management factor, Climate data, topography, Land use/Land cover, field management practices,	Modified Universal Soil Loss Equation	Erosion, prediction of sediment yield, simulation of individual storm events	Calibration is complex, shows significant difference with measured sediment yield in many watersheds	No	Yes	No	No	(Chandramohan et al., 2015)
3	RUSLE	Revised Universal Soil Loss Equation	(Renard et al., 1991)	Annual	Catchment/ Hillslope	High	Climate data, topography, Land use/Land cover, field management practices, crop management factor	Revised Universal Soil Loss Equation	Erosion, process-based auxiliary components (e.g., time-variable soil erodibility, plant growth, residue management)	Slope length factor may not be suitable for more than 25° , does not estimate gully- or stream-channel erosion caused by raindrops	No	Yes	No	No	(Le Roux et al., 2008)
4	MOSES	Modular Soil Erosion System project	(Charles R. Meyer et al., 2001)	Annual	Catchment/ Hillslope	High	Climate data, topography, Land use/Land cover, field management practices, crop management factor	Enhanced Revised Universal Soil Loss Equation (RUSLE2), Wind Erosion Prediction System (WEPS) model	Wind erosion, water erosion sediment yield, runoff	Does not consider gully erosion	No	Yes	No	No	(Charles R. Meyer et al., 2001)
5	SEDD	Sediment Delivery Distributed	(Ferro and Porto, 2000)	Annual	Basin, large catchment	High	DEM, a land use Map, climate, human influence	Universal Soil Loss Equation	Basin sediment yields	Model reliability decreases from the annual scale to the event scale	No	Yes	No	No	(Ferro and Porto, 2000)
6	EPM	Erosion Potential Method	(Dragičević et al., 2017)	Annual	Field	High	Climate data, topography, area of catchment, stream network, soil erodibility coefficient	Analytical equation for spatial and temporal variation measurement	Retention coefficient Erosion intensity, sediment production sediment transport	Performance subjected to the specific characteristics and sedimentary regime of the study area	No	Yes	No	No	(Ahmadi et al., 2020)
7	TCRP	Tillage-Controlled Runoff Pattern model	(Takken et al., 2001)	Event/ Annual	Field	Low	DEM, a land use map, and the major tillage direction on each field	Incorporated with LISEM model, Generalized erosion-deposition mass balance, Dynamic Erosion concept eqn.	Runoff pattern, erosion patterns, runoff network	Local depressions that may exist in a DEM need to be removed making runoff pattern more complicated	No	No	No	No	(Takken et al., 2001)
8	TMDL	Total Maximum Daily Load	USA EPA (1991)	Annual	Catchment	High	Channel network, Groundwater exchange,	Modified Kilinc-Richardson equation for soil erosion, advection-	Multi-dimensional, Provides amount of	Transport capacity must be converted into erosion	No	No	No	No	(Thaxton et al., 2004)

							Topography, unit discharge rate, soil cropping factor, conservation factor	dispersion equation for in-channel sediment transportation, general transport equation for overland sediment transport	sediment and nutrients	coefficient. , determining the interdependent factors is difficult.					
9	SLEMSA	Soil Loss Estimation Model for Southern Africa	(Elwell, 1978)	Annual	Field	High	Climate data, topography, vegetation, human influence	ELWELL equation $Z = K*X*C$ Where K (Mean annual soil loss index, X (Topographic Factor), C (Crop cover/management factor)	Soil erosion, decision on land management techniques	High sensitivity to the input factors	No	Yes	No	No	(Albaladejo Montoro and Stocking, 1989)
10	PSIAC	Pacific Southwest Inter-agency Committee Method	(PSIAC, 1968)	Annual	Catchment/Field	High	Surface geology, soil types, Climate, slope, stream network, land cover/land use	Gravelius Equation, Horton Equation, Kiripich Equation, Drainage Density Equation, upland erosion= 0.25SSF (SSF: soil surface factor), Channel erosion =1.67SSFg (SSFg: Gully erosion factor)	Upland erosion, Channel erosion, sediment deposition	Model sensitivity to changes of different factors under different conditions	Yes	Yes	Yes	Yes	(De Vente et al., 2013)
11	E_{30}	Soil Erosion at 30° slope	(Kiyoshi, 1993)	Annual	Watershed	Low	Land use/Land cover maps, topography	$E = E_{30} * (S/S_{30})^{0.9}$ E: rate of soil erosion; E30: rate of soil erosion at 30⁰ slope; S30: 300 slope	Soil Erosion	Model applies only to hilly regions having undulant topography and steep slopes. Does not take into account soil factors (crirtical for erosion processes)	No	Yes	No	No	(Kiyoshi, 1993)
12	WaNuLCAS	water, nutrient and light capture in agroforestry system	(Van Noordwijk and Lusiana, 1998)	Annual	Watershed /field	High	Land use/Land cover, Climate data	USLE	Soil erosion, crop yield	The erosion component is not well developed and integrated with crop yield	Yes	No	No	No	(Onsamrarn et al., 2020)
13	SCUAF	Soil Changes Under Agroforestry	(Magcale-macandog, 2002)	Annual/ Seasonal	Watershed /field	High	Crop, soil physical and chemical properties	USLE	Predict soil changes under different agroforestry systems	Erosion component is not well tested	No	No	No	No	(Magcale-macandog, 2002)

G: Generation; T: Transportation; D: Deposition; Developer/year: references for model manuals and first research articles describing the respective model

3.2.2. Conceptual Models

Conceptual models are based on the sediment and runoff continuity equations, and basically take a position between physically based and empirical models (Beck, 1987). Unlike empirical models, conceptual models reflect the process governing the system behavior. The primary focus of conceptual models has been to estimate sediment yield based on the concept of unit hydrograph (Chmelová and Šarapatka, 2002). Therefore, they typically consider the most critical catchment characteristics and corresponding soil erosion processes, however, without describing the details of these processes and interactions that would require data on temporal and spatially distributed catchment details (Sorooshian, 1991). As a result, conceptual models can be used to simulate quantitative and qualitative impacts of land use changes on soil erosion and sediment yields without having to be parametrized with detailed catchment in-formation.

Jakeman et al. (Jakeman and Hornberger, 1993) noted that conceptual models tend to have issues related to the identifiability of their parameter values since those values were generally obtained during model calibration with observed values (Abbott et al., 1986) . (Sorooshian, 1991) identified the direct relationship between conceptual model complexity and model identification. The calibration procedure for medium complex models can find only the local best fit although there may be many other local conditions with optimum parameter sets. This problem can be resolved by reducing the number of parameters that have to be estimated through calibration and increasing the number of parameters that can be estimated based on prior knowledge of the system (Kleissen, 1990). Such an approach will reduce the goodness of fit to the calibration data. The lack of parameter values for conceptual models means limiting the physical interpretability of parameters (Pechlivanidis et al., 2011). Though more complex models tend to offer a better fit to calibration data they also carry the risk of over-fitting when calibration data are limited (Onof and Wheater, 1993).

Most of the conceptual models use equations from empirical approaches (Table 2.4). The empirical models USLE and MUSLE, for example, are implemented in conceptual models such as APSIM (modeling framework), SWIM, RillGrow, SWRRB, and LASCAM for estimating soil erosion. These conceptual models can predict the temporal and spatial distribution of soil detachment and sedimentation at a field scale depending on crop and soil management at daily time steps. Among these models, APSIM and IQQM are continuous simulation models predicting both overland and channel sediment generation, transportation and deposition, as well as rainfall-runoff associated nutrient loss and soil changes. A few models such as APSIM, AGNPS, and AGNPS-UM are event-based models to predict soil erosion under complex agriculture systems from smaller scales (hill-slopes) to large (catchment) scales (Table 2.4).

Table 2. 4. Conceptual soil erosion models

Sr. No.	Model	Description	Developer /year*	Scale		Input		Governing Equations	Model Capabilities	Model Limitations	Overland Sedimentation			Channel Sedimentation Generation	Source
				Temporal	Spatial	Demand	Variables				G*	T*	D*		
1	APSIM	Agricultural Production Simulator	(McCown et al., 1996)	Daily	Field	High	Climate, topography, land use, crop, field management practices	Modified USLE, soil water balance equation	Erosion, *	Intensive calibration and validation required	Yes	Yes	Yes	No	(Basche et al., 2016)
2	RillGrow	RillGrow	(Favis-Mortlock, 1996)	Abstract	Plot	High	Meteorology, Digital Terrain Model	S-Curve stream power based equations	Formation and simulation of rill network	Depends on single storm events; Low potential for integration with GIS	Yes	Yes	Yes	No	(Favis-Mortlock, 1996)
3	SWAT	Soil and Water Assessment Tool	(Arnold et al., 1998)	Daily	Regional to watershed	Medium	Climate, soil characteristics, topography, land use / Land cover	MUSLE, Manning's equation, SCS Curve Number, Bagnold's stream power Concept, Continuity equation	Hydrological assessments, pollutant loss studies, water erosion, sediment yield	Weak in stream channel degradation and sediment deposition analysis, inadequate data availability for calibration and validation	Yes	Yes	Yes	Yes	(Aga et al., 2020)
4	SWIM	Soil and Water Integrated Model	(Krysanova et al., 1998)	Daily	Watershed	Medium	Climate, soil characteristics, land cover, crop types	water balance equation, MUSLE, SCS Curve Number,	Simulation of runoff, soil erosion, sedimentation *	relatively complex, no simulation of gully erosion	Yes	No	No	No	(Krysanova et al., 2007)
5	IQQM	Integrated Water Quality and Quantity Model	(Simons et al., 1996)	Daily	Watershed	Medium	Topography, river system configuration, evapotranspiration	conceptual Sacramento model, QUAL2E model	Rainfall-runoff generation, *	No erosion or sediment generation simulation	Yes	No	No	Yes	(Simons et al., 1996)
6	CAESAR	Cellular Automaton Evolutionary Slope and River model	(Murray and Paola, 1994)	Annual	Catchment	High	DEM, Rainfall, flow parameters, slope processes, bedrock depth, value of Manning coefficient	Einstein equation, Wilcock & Crowe equations	Erosion,sediment transport & deposition	No rainfall-runoff interactoin	Yes	Yes	Yes	Yes	(Coulthard et al., 2000)
7	TOPMODEL	Topography based hydrological MODEL)	(Kirkby, 1997, 1975)	Daily	Hillslope	Medium	DEM, landform features, soil characteristics, geology, vegetation, and hydrological characteristics	Sediment transport capacity, continuity equation	Soil moisture deficit, rainfall-runoff, Simulation of surface/subsurface hydrology; sediment yield and transport	Suitable only for shallow homogenous soil watersheds	Yes	No	No	No	(Beven et al., 1984)
8	WILSIM	Web-based Interactive Landform Simulation Model	(Luo et al., 2004)	Abstract	Watershed	High	DEM, Topography, Rainfall, flow parameters, slope	Cellular automata (CA) algorithm	simulation offers an ideal tool for understanding the complex effects of a variety of physical and geological processes and erosion	Many details of the physical process are not included in the model.	Yes	No	No	Yes	(Luo et al., 2006)

9	SWRRB	Simulator for Water Resources in Rural Basins	(Williams et al., 1985)	Daily	Catchment	High	Rainfall data, soil characteristics, Land use	MUSLE, Sediment balance equation	Simulation of Stream flow, Rainfall-runoff, Sedimentation and plant growth on daily time steps	Uncertainties in model parameter estimations, based on many assumptions leading to uncertainties	Yes	No	No	Yes	(Williams et al., 1985)
10	LASCAM	Large Scale Catchment Model	(Sivapalan et al., 1996)	Daily	Catchment	High	Sediment load, runoff, salt fluxes	USLE, Stream sediment capacity	Simulation of hydrology, erosion,	During calibration low quality of sediment and nutrient predictions	Yes	Yes	Yes	Yes	(Sivapalan et al., 2002)
11	AGNPS	Agricultural Non-Point Source pollution model	(Young et al., 1989)	Daily	Small- to medium-sized watersheds	High	Climate, topography, soil characteristics, Land use	SCS Curve Number, USLE, Foster equation	Soil erosion, sediment transport and depositing,	Does not simulate sub-surface flow, only suitable to small-medium catchments	Yes	No	No	Yes	(De Vente et al., 2013)
12	ACRU	Agricultural Catchment Research Unit	(Schulze, 1995)	Daily	Small catchments (<10 km^2)	Low	Climate, soil, land use crop	SCS equation, catchment curve number,	Simulate runoff, erosion and sediment yield, land use and climate impacts, seasonal crop yield	Require extensive GIS pre-processing	Yes	No	No	Yes	(Aduah et al., 2017)
13	STREAM	Sealing, Transfer, Runoff, Erosion, Agricultural Modification model	(King et al., 2005a)	Event	Catchment to watershed	High	rainfall, temperature, topography, soil (water holding capacity), land cover	USLE	Simulates land use impacts, erosion, sedimentation	applicable to single rainfall events	Yes	Yes	Yes	Yes	(King et al., 2005b)
14	AGNPS-UM	Agricultural Non-Point Source pollution model,	(Grunwald et al., 1997)	Daily	Catchment to watershed	High	Climate, topography, soil characteristics, Land use	USLE-M	Management decisions on water and sediment yields	Rely on single storm event; data intensive	Yes	No	No	Yes	(Grunwald et al., 1997)

*additional model capabilities besides soil erosion; G: Generation; T: Transportation; D: Deposition; Developer/year: references for model manuals and first research articles describing respective model

3.2.3. Physically based Models

In general, physically based soil erosion models are based on the fundamental concepts of physics using conservation of momentum, energy, and mass as governing equations (Kandel et al., 2004a; Mohamadi and Kavian, 2015) that are solved by various numerical techniques. Thus, these models consist of multiple equations and algorithms and a large number of parameters to simulate and predict the dynamics of soil erosion and sedimentation rates. They explicitly simulate the water fluxes, e.g., overland flow based on the kinematic wave theory (Lighthill and Whitham, 1955), and apply the kinematic wave theory based on continuity and momentum equations. The continuity equation refers to the balance between inflow into the system and change in system storage and the momentum equation represents the pressure gradient between energy gradient and surface slope. Other most famous approaches for simulating the water fluxes include the Manning's and Chézy's equations in large watersheds (Table 2.5).

In general, the equations of individual model components in physically based models are based on a large number of assumptions that may not be relevant in the real world. These governing equations were often developed under controlled conditions using continuous data observed at single observation points or small spatial scales (Beven and Kirkby, 1979). In practice, these equations are applied for grid cells representing much larger areas of water-sheds with varying physical conditions. Corresponding assumptions required for up-scaling point-based observations may compromise the physical significance of models (Seyfried and Wilcox, 1995). (Merritt et al., 2003) pointed out that there is not enough evidence on the suitability of these equations for modeling water erosion beyond a small field scale. (Pechlivanidis et al., 2011), therefore, suggested applying simplified computation techniques to represent individual processes which avoid unwanted deflection from real field scenarios and additional uncertainties. In practice, parameters used in physically based models should be calibrated with observed data that, on the other hand, creates a lack of identifiability analysis of optimum parameters and distinctiveness of best fit to the veracity of modeling outputs (Blöschl and Sivapalan, 1995). Model comparisons illustrate that the application of physically based models (e.g., AGNPS or PESERA) does not necessarily result in lower uncertainties compared to more simple structured empirical models such as USLE-type algorithms.

Physically based field-scale models such as EPIC, EGEM, CREAMS, EROSION 2D/3D, GUEST, GLEAMS, MEFDIS, MEDALUS, PERFECT, PEPP-HILLFLOW, etc., are more capable of responding to event-based or continuous storms to simulate surface run-off, soil detachment, transportation, and sediment yield (Table 2.5). The EPIC model con-siders the effect of several best management practices (BMPs) related to crop, soil, and nutrient management on soil erosion and soil productivity. CREAMS is another model that is used for describing the hydrology, erosion, and sediment size distribution as well as changes in soil depth, chemical, nutrient, and sediment yield for field-scale croplands. Productivity, Erosion and Runoff, Functions to Evaluate Conservation Techniques (PER-FECT) is a dynamic model suitable for event-based analysis of soil erosion and surface runoff over a small scale. This model can also be integrated with a GIS tool for visualization of results. The main disadvantage of this model is that it overestimates the outputs of surface runoff and surface water retention capacity as influenced by complex tillage pat-terns and tillage directions.

Table 2. 5. Physically based soil erosion models

Sr. No.	Model	Description	Developer /year*	Scale		Input		Governing Equations	Model Capabilities	Model Limitations	Overland Sedimentation			Channel Sedimentation Generation	Source
				Temporal	Spatial	Demand	Variables				G*	T*	D*		
1	ANSWERS	Areal Nonpoint Source Watershed Environment Response Simulation	(Beasley et al., 1980)	Event	Regional to small catchment	High	Climate, soil characteristics, topography, land use, drainage network, field management practices	USLE, steady-state sediment continuity equation, Modified Yalin equation, Foster equation	Erosion, sediment yield, runoff, peak flow rate, nutrients,*	Relies on single storm Event, consider erodibility as time constant parameter	Yes	Yes	Yes	No	(Bouraoui and Dillaha, 1996)
2	EPIC	Erosion-Productivity Impact Calculator	(J. R. Williams et al., 1989)	Daily	Plots to field-sized areas	High	Hydrology, meteorology, erosion, nutrients, plant growth, soil temperature, and tillage.	curve number equation, Onstad-Foster equation, USLE, MULSE	Surface runoff, sediment yield, soil erosion *	Applicable to only field scale, less incorporation with GIS tools	Yes	Yes	Yes	Yes	(Pumijum nong and Arunrat, 2012)
3	ANSWERS-continuous	Areal Nonpoint Source watershed Environment Response Simulation-Continuous	(Bouraoui and Dillaha, 1996)	Event	Regional to small catchment	High	Climate, soil characteristics, topography, land use, drainage network, field management practices	USLE, Modified Yalin equation, Foster equation, Manning's equation	Erosion, sediment yield, *	No simulation of channel sediment	Yes	Yes	Yes	No	(Bouraoui and Dillaha, 1996)
4	EGEM	(Ephemeral Gully Erosion Model	(Watson et al., 1986)	Event	Field to small catchment	Medium	Rainfall, soil characteristics, Topography	Physical-process equations CREAMS empirical relationship	Annual estimation of Transient gully erosion	Requires intensive watershed information	Yes	No	No	Yes	(Woodwar d, 1999)
5	DWSM	Dynamic Watershed Simulation Model	(D. K. Borah, 1989)	Event	Catchment	High	Stream network, watershed hydrology, water quality, land use	continuity equation	Simulation of erosion, runoff, erosion, sediment yield *	Slow computing speed, uncertainties in input parameter data	Yes	Yes	Yes	Yes	(D. K. Borah, 1989)
6	CREAMS	Chemicals, Runoff and Erosion from Agricultural Management Systems	(Knisel, 1982)	Monthly	Plot to Field	High	Climate, vegetation, cultural practices	Foster equation, MUSLE, SCS Curve Number, Yalin's equation	Erosion, sedimentation, runoff, from agricultural area	suitable only for field scale, low potential for GIS integration	Yes	Yes	Yes	No	(Williams et al., 1985)
7	EROSION-2D/3D	EROSION	(Schmidt, 1991)	Event	Field / small catchment	High	Climate, soil characteristics, topography	Mass balance equation	Simulation of erosion	Requires extensive computational efforts	Yes	Yes	Yes	Yes	((Schmidt et al., 1999)
8	EUROSEM	European Soil Erosion Model	(R P C Morgan et al., 1998)	Event	Catchment	High	Climate, soil characteristics, land use, topography	Dynamic mass balance equation	Simulation of erosion, sediment yield, deposition and runoff	Lower accuracy for large catchments	Yes	Yes	Yes	No	(Khaleghp anah et al., 2016)
9	GUEST	Griffith University Erosion System Template	(Hairsine and Rose, 1991)	Steady State	Plot	High	Climate, watershed soil characteristics, runoff, topography	Mass balance equation, Deposition Equation, Rose equation	Simulation of runoff, sedimentation	Low potential for GIS integration, high data requirement	Yes	Yes	Yes	No	(R.K. Misra and Rose, 1996)

10	IDEAL	Integrated Design and Evaluation of loading Models	(Singh and Frevert, 2006)	Event	Catchment	High	Climate, soil characteristics, land Use and land cover	MUSLE	Sedimentation yield, erosion, *	Rely on single storm events	Yes	Yes	Yes	Yes	(Singh and Frevert, 2006)
11	GLEAMS	Groundwater Loading Effects of Agricultural Management Systems modelling system	(Leonard et al., 1987)	Daily	Field scale and small catchment	High	Climate, land use, field management and cultural practices	MUSLE, Foster equation	Simulation of erosion, sediment yield, *	Uncertainties in parameter estimations and model validation	Yes	Yes	Yes	No	(Garnier et al., 1998)
12	KINEROS	KINematic runoff and EROSion model	(Woolhiser et al., 1990)	Event	Small Catchment, hillslope areas	High	Rainfall, soil, topography, land cover, drainage network and channel geometry	Bennett Mass balance equation, sediment transport approach, Kinematic wave equations	Erosion, sediment yield, peak runoff rate, runoff	Runoff estimations are based on single storm events without considering sub-surface flows	Yes	Yes	Yes	No	(Tajbakhsh et al., 2018)
13	LASCAM	Large Scale Catchment Model	(Viney and Sivapalan, 1999)	Daily	Catchment	High	Climate, Surface topography, DEM, streamflow and sediment data	USLE	Erosion, sediment yield, nutrients	Uncertainties in the model outputs	Yes	Yes	Yes	Yes	(Sivapalan et al., 2002)
14	MEFIDIS	Modelo de ErosaoFIsico e DIStribuido	(Seixas et al., 2005)	Event	Field scale and small catchment	High	Climate, topography, Surface topography, DEM, catchment characteristics, streamflow and sediment data	Diffusive wave equation, Foster equation Kinetic rainfall energy equation, sediment transport capacity approach	Erosion, runoff	Soil erosion based on extreme rainfall events, low potential for GIS integration	Yes	Yes	Yes	Yes	(Seixas et al., 2005)
15	MEDALUS	Mediterranean Desertification and Land Use research programme Model	(Kirkby, 1998; Kirkby et al., 1998b)	Event	Field scale and small catchment	High	Climate, soil, Land cover/ land use, Topography	Mass momentum approach	Erosion, impact of land use changes	Rely only on recent data for inputs	Yes	Yes	Yes	Yes	(Lamqadem et al., 2018)
16	PERFECT	Productivity, Erosion and Runoff, Functions to Evaluate Conservation Techniques	(Littleboy et al., 1989)	Daily	Field	High	Climate, soil, crop, tillage	MUSLE	Erosion, runoff, crop yield	Detailed information on crop management and tillage practices	No	No	No	No	(Littleboy et al., 1992b)
17	PEPP-HILLFLOW	Process orientated Erosion Prediction Program	(Schramm, 1994)	Event	Field scale and small catchment	High	Climate, soil characteristics, Land cover/ land use, Topography, nutrients	Sediment continuity equation, Foster equation, Yang's unit stream power method	Runoff, Erosion	Rely on single storm Event, intensive data requirement	Yes	Yes	Yes	Yes	(Schramm, 1994)
18	RUNOFF	RUNOFF	(D. K. Borah, 1989)	Event	Small Catchment	Low	Rainfall, soil characteristics, topography, land cover,	Splash erosion, flow rate equations	Erosion, runoff, sediment yield	Uncertainties in input parameter estimations and model validation	Yes	Yes	Yes	No	(D. K. Borah, 1989)

							drainage network and channel geometry								
19	PESERA	Pan-European Soil Erosion Risk Assessment	(Kirkby et al., 2004)	Annual	Regional	Medium	Climate, soil characteristics, land cover, topography	Mass and momentum balance equations,	Runoff, erosion, sediment yield, crop yield	Flow routing is not well developed	Yes	Yes	Yes	No	(Alewell et al., 2019)
20	SHE/ SHESED	Systeme Hydrologique Europian/- Systeme Hydrologique Europian Sediment	(Abbott et al., 1986)	Event	Hillslope to Catchment	High	Rainfall, soil characteristics, topography, land cover	Mass and momentum balance equations, Yalin's equation	Erosion, sediment transport, sediment yield	No simulation of gully erosion	Yes	Yes	Yes	No	(Abbott et al., 1986)
21	WEPP	Water Erosion Prediction Project	(Laflen et al., 1991)	Daily	Hillslope to Catchment	High	Climate, soil, topography, land use, field management and cultural practices, channel network	Steady-state sediment continuity equation, Foster equation	Runoff, erosion, sediment yield	Large number of input parameters, neglect the simulation in permanent channels	Yes	Yes	Yes	Yes	(Brooks et al., 2016)
22	WESP	Watershed erosion simulation program	(Lopes, 1987)	Event	Small Catchment	Medium	Climate, soil, topography, channel network	Kinematic wave equations,	Simulation of runoff and erosion *	Intensive computation of input parameters	Yes	Yes	Yes	Yes	(Lopes, 1987)
23	WATEM/ SEDEM	Water and Tillage Erosion Model/Sediment Delivery Model	(Oost et al., 2000)	Annual	Field	Low	Climate, soil characteristics, land cover, flow network	RUSLE	Erosion, tillage erosion, sedimentation	Require high quality detailed watershed information	Yes	Yes	Yes	Yes	(Panagos and Katsoyiannis, 2019)
24	SEMMED	Soil Erosion Model for Mediterranean Areas	(Panagos and Katsoyiannis, 2019)	Annual	Regional scale	Medium	DEM, climate, soil characteristics, channel network and geometry	Distributed transport capacity	Simulate the distributed character of the erosion process, predicts soil loss	Sensitive to storage capacity, soil moisture, soil detachability index	Yes	Yes	Yes	No	(De Jong et al., 1999)
25	SIMWE	Simulation of Water Erosion	(Thaxton et al., 2004)	Event	Catchment	High	Rainfalls, surface roughness, DEM	Saint Venant equation for continuity of flow, Manning's n value.	Erosion, gully Formation, sediment transport and deposition *	Require high quality detailed watershed information	Yes	Yes	Yes	No	(Fernandes et al., 2017)
26	RHEM	Rangeland Hydrology and Erosion Model	(M. A. Nearing et al., 2011)	Event	Field scale and small catchment	High	Climate, soil characteristics, watershed characteristics	Sediment transport equation	uRnoff, erosion, sediment yield	less suitable for simulation of rangeland surfaces	Yes	Yes	Yes	No	(Hernandez et al., 2017)
27	TOPOG	TOPOG	(Vertessy and Wilson, 1990)	Daily	Hillslope to Catchment	High	Climate, soil, topography, Land cover	Equations for sediment transport in channels	Erosion	Extensive input data requirements and a high number of physical parameters (complex)	Yes	Yes	Yes	No	(Maftei et al., 2019)

*additional model capabilities besides soil erosion; G: Generation; T: Transportation; D: Deposition; Developer/year: references for model manuals and first research articles describing respective model

3.2.4. Remote Sensing (RS) and GIS-based soil erosion modeling

Remote Sensing data combined with GIS tools provide the powerful capabilities for mapping soil characteristics and soil resources over high spatial and temporal resolution in a timely and cost-effective way (Lu et al., 2004). Soil erosion models can be incorporated into GIS tools and combined with RS data. RS derived climate data, land use/land cover information, and their integration with GIS can be used for soil erosion modeling (A. Pandey et al., 2007). Remote sensing based digital elevation/terrain model (DEM/DTM) is an important tool to provide inputs to the soil erosion models, catchment rainfall/runoff relationship development, and sedimentation processes (DeVantier and Feldman, 1993; Jenson and Domingue, 1998; Walker and Willgoose, 1999). Various GIS techniques (QGIS, ArcGIS) use Digital Elevation Models (DEM) and can derive multiple variables for topographical parameterization such as slope, aspect ratio, drainage, stream and catchment delineation, surface flow, and soil erodibility factor (Coveney and Fotheringham, 2011).

Many well-known soil erosion models i.e., USLE (Universal Soil Loss Equation, 1965) (Liu et al., 2018), RUSLE (Revised Universal Soil Loss Equation, 1997) (Karamage et al., 2017), SEMMED (Soil Erosion Model for Mediterranean Regions, 1999) (De Jong et al., 1999), PESERA (Pan-European Soil Erosion Risk Assessment, 2003) (De Vente et al., 2013), EUROSEM (European Soil Erosion Model, 1993) (R. P.C. Morgan et al., 1998), and EGEM (Ephemeral Gully Erosion Model, 1999) (Woodward, 1999), integrated with RS and GIS techniques, have been widely used.

The use of GIS and RS for soil erosion and sedimentation modeling may involve certain consequences including multiple data sources based on vast data requirements, computing expertise for model re-scaling and data reliability issues, and complex verification algorithms of model outputs (Karydas and Panagos, 2016).

3.3. Description of Selected Models with respect to Plot Scale Simulations

A list of different soil erosion models is presented in section 3.3. These models vary in their range of complexity, data requirements, the scale of application, and key limitations. This section aims to provide a brief introduction to models selected on their applicability to a plot/field scale. The shortlisted models are reviewed in terms of their objective, model structure, components, and their assimilation, and model calibration ease and parameter requirements are presented in this section.

The review of models is limited to those models with strict consideration of soil erosion generation at a plot or field scale. Therefore, many other commonly applied models, for example SWAT, EUROSEM, etc., are not discussed in this section (Table 2.6). In order to assess the model capabilities to simulate soil erosion, application examples of selected models in different climatic zones were reviewed and summarized in Table 2.6. The Nash–Sutcliffe efficiency method was the most commonly used method for evaluation of model performance. Further, Root mean square error, coefficient correlation, average absolute error, and coefficient of determination were commonly applied measures.

Most studies report a sensitivity of simulated sediment deposition to different environmental and management factors, such as rainfall, crop management factors, soil physical properties, and vegetation cover. Selected models were tested at field or plot scales under different cropping systems and field conditions. Calibration of field scale models based on data from fields that are characterized by a high spatial heterogeneity of topography and soil types is more accurate than using spatial averaged data from larger catchment areas. Most of the field scale models are based on one-dimensional equations (Saint Venant equation or Kinematic wave theory) for estimation of overland flows, there-by limiting their capabilities for spatially distributed modeling. Only a few models, such as WEPP, TCRP, and CREAMS, also represent the water movement through the unsaturated part of the soil profile which influences the runoff on hillslopes (Table 2.6).

Table 2. 6. Examples of applications of some selected field scale soil erosion models

Sr. No.	Model	Description	Spatial dimension	Model type	Study area	Objective	Input data used	Method used for evaluation	Conclusion	Remarks	Reference
	EPM	Erosion Potential Method	1D	Dynamic	Alfenas Municipality, (437ha)	Simulation of surface runoff, soil erosion, comparing results with RUSLE of SLT	DEM, climate data, soil characteristics	Sediment retention coefficient, RMSE, correlation-coefficient	Correlations of the potential values of soil erosion between EPM and RUSLE showed a similar pattern for the different land management types and land uses despite the different orders of magnitude	For calibration, EPM requires experimental validation, which would be subjected to heterogeneity of crop and soil in the field	(Tavares et al., 2019)
2	TCRP	Tillage-Controlled Runoff Pattern model	2D	Dynamic	Multiple sites	Sediment fluxes, deposition processes in a 2-D spatial context	sediment deposition equations	Correlation coefficient	Model is capable of simulating both spatial pattern and size selectivity of deposition pattern in tilled fields	Understanding and representation of sediment delivery and deposition need to be improved	(Van Oost et al., 2004)
3	WEPP	Watershed Erosion Prediction Project	2D	Dynamic	Demonstration farm, Ratchaburi province, Thailand	Performances of the WEPP under conservation cropping system	Monthly rainfall, Land use map, Soil map, DEM, Daily Sediment	NSE	WEPP model predicted lower values of runoff and sediment yield. WEPP coupled with MIKE SHE/MIKE 11 capable to simulate soil losses in different conservation practices	Satisfactory Performance for sediment yield estimation at small scale	(Heydarnejad et al., 2020)
4	APSIM	Agricultural Production Simulation	1D	Dynamic	16 plots, 52 m^2 (4 m × 13 m) in area each plot	Modeling effects of tillage on soil water dynamics	Daily temperature, daily rainfall, Tree zoning	R^2, NSE, RSR	APSIM is adequate for agroforestry system	APSIM requires modification in soil erosion component	(Dilla et al., 2020)
5	EPIC	Erosion-Productivity Impact Calculator	1D	Dynamic	South-central Chile	Simulation of soil erosion	DEM, climate data, soil characteristics	correlation coefficient, RMSE	Calculated rates of soil erosion was overestimated as slope segment is relatively difficult to decide	EPIC predicts two times more soil erosion under wheat and conventional tillage comparing to WEPP and USLE	(Stolpe, 2005)
6	CREAMS	Chemicals, Runoff and Erosion from Agricultural	2D	Dynamic	Finland	Predicting field-scale runoff	Mean daily temperatures and rainfall, Evapotranspirati	AERR, RMSE, NSE	Snow accumulation and snowmelt description, adjustable albedo	SCS curve number can be introduced for more	(Rekolainen and Posch, 1993)

		Management Systems				and erosion, modify the model for Finnish conditions	on, surface albedo, leaf area index,		introduction into CREAMS improved simulations of runoff volumes	physically based representation of runoff in alley cropping system	
7	GUEST	The Griffith University Erosion System Template	1D	Dynamic	Tilting flume (6 x 1) m.	Evaluation of GUEST and WEPP for determining sediment transport capacity	Soil samples, tilting flume	ME, R^2, RMSE	GUEST model predicted higher values of erosion than WEPP, this difference can be due to the particle size distribution and rill morphology	GUEST tends to overestimate sediment yield in heterogeneous soil condition	(Mahmood abadi et al., 2014)
8	PERFECT	The Productivity, Erosion and Runoff, Functions to Evaluate Conservation Techniques	1D	Dynamic	Plot scale, Queensland	Simulates interactions between soil type, climate, and fallow management strategy and crop sequence.	Initial soil moisture, soil characteristics, topography, Landuse	R^2	PERFECT does not consider rainfall intensity and represents less accurate soil erosion on daily time steps.	The validated model can be coupled with soil and long-term climate databases to simulate probabilities of production and erosion risks due to climatic variability.	(Palosuo et al., 2011)

R2: Coefficient of determination, NSE: Nash-Sutcliffe efficiency, RSR: RMSE-observations standard deviation ratio, RMSE: Root Mean Square Error, ME: Model efficiency, AERR: average absolute error

3.3.1. Erosion Potential Method, EPM

Erosion Potential Method (EPM) is an empirical model to simulate water erosion from fields to small catchments, using input data related to meteorology and the matrix of the catchment physical characteristics. The model has been widely applied worldwide. It contains an advanced classification procedure using four characteristics including erosion coefficient, land use coefficient, soil erodibility, and mean slope in different land units (Ahmadi et al., 2020). (Kouhpeima et al., 2011) state that EPM is a method for easy and rapid analysis of erosion risk and sedimentation. The accuracy of results depends on the values of erosion coefficients. Moreover, EPM considers only four factors for erosion assessment and can be applied to small areas where database layers are limited. EPM integration with GIS and remote sensing could be a useful technique in the identification of soil loss and sedimentation in areas with insufficient sediment gauging stations (Ali et al., 2016). The over-/under-prediction limits of EPM simulations are within 13 percent from the measured values and are considered to have acceptable accuracy for soil loss simulations at the catchment scale (da Silva et al., 2007; S. Pandey et al., 2007).

3.3.2. Tillage-Controlled Runoff Pattern model, TCRP

The TCRP model has been evaluated in different environments globally, mainly for the prediction of runoff patterns with the flow along the direction of plow lines in tilled fields within a catchment. This model requires a digital elevation model, land use maps, and tillage orientation as inputs. The model creates a tillage-controlled runoff pattern along with a topographic controlled runoff pattern. The use of the first one in event-based deterministic models results in a much better level of accuracy for runoff and erosion pat-terns with field observations. Model simulations show that tillage information should be included when estimating runoff directions if erosion pattern accuracy is under question. (Souchere et al., 1998) proposed that to analyze the tillage impact on runoff in a spatially distributed water model, each cell must be assigned to a tillage direction. This results in complexities as flow lines may cross each other and ditches may exist on the field. (Souchere, 1995) solved these problems by changing the runoff direction manually and assuming the runoff is always in the direction of tillage. However, it would be laborious for large catchments to be modeled.

The TCRP model was developed using raster language to specifically integrate with the GIS tool (Wesseling et al., 1996). The model requires surface physical characteristics, DEM, land use maps, and tillage direction information as inputs. The maps should have an area larger than that of the catchment to be modeled because catchment boundaries can be defined after only the assessment of runoff patterns.

3.3.3. Soil Loss Estimation Model for Southern Africa, SLEMSA

SLEMSA was developed by (Elwell, 1978) in Zimbabwe as a framework for estimating local soil losses by using details of local environmental conditions driving soil erosion process i.e., climate, soil types, topography, soil cover, and field management practices (Elwell and Stocking, 1982; Kinama et al., 2008). The SLEMSA modeling approach consists of four major steps: (1) identify major control variables (rainfall energy, interception, etc.), for which the values are easily measured and have a rational physical explanation, (2) develop a relationship, called submodels, be-tween selected variables and soil losses, (3) formulate the model to relate these submodels, (4) test the model (Elwell and Stocking, 1982). (Heydarnejad et al., 2020) examined SLEMSA in series of tests, with careful monitoring of controlled variables on selected plots; errors of 9 to 18 percent were noted. SLEMSA claims to be simpler relatively to the USLE as it is less data demanding with high extrapolation capabilities (Albaladejo Montoro and Stocking, 1989). GIS can be used to calculate SLEMSA control variables that upon formulation provide potential soil losses within the catchment (Breetzke et al., 2013). A study of SLEMSA in mountainous terrain by (Hudson, 1987) indicates the sensitivity of potential soil loss to both slope steepness and rainfall erosivity resulting in an overestimation of soil loss with steep slopes and high rainfall intensities (Le Roux et al., 2008).

3.3.4. Agricultural Production Simulation, APSIM

APSIM, a dynamic conceptual modeling platform, was developed by the Agricultural Production Systems Research System Unit (APSRU) in Queensland. APSIM modeling platform has been evaluated worldwide in different environmental conditions ranging from interpretation of on-farm experiments to risk assessment of a range of alternative management options (Masere and Worth, 2015) mainly to simulate the crop production in relation to climate, soil erosion, and field management practices while identifying long-term solutions for natural resource management issues at field scale using input data provided at daily time steps (McCown et al., 1996; Teixeira et al., 2018). Since APSIM offers many modules (generally categorized as biological and environmental modules), the erosion model is capable to simulate the impact of erosion on the soil profile as soil loss occurs. The erosion module remains unaware of the impact of other modules on the profile. The estimation of daily soil loss is performed by either of two submodels (1) Freebairn and (2) Rose (McCown et al., 1996). The lateral one uses the USLE equation (Freebairn and Wockner, 1986; Littleboy et al., 1989). The module was revised to consider runoff and land cover, which can be affected by management within the APSIM model. The soil erosion measurements required for calibration are based on the runoff volume, soil cover, soil erodibility, and slope-length factor along with management practices. A different module within APSIM provides the values of these factors i.e., the surface cover is provided by the soil organic matter module, and the SWIM module provides surface runoff. (Basche et al., 2016) have successfully calibrated and validated the APSIM model to predict runoff and sediment yield. Further, the tested APSIM model was implemented for soil loss based risk management and supporting practices. However, the use of this model is only recommended when sufficient data is available. Notably, APSIM has high input demand; most uses require extensive field investigations.

3.3.5. RillGrow

The RillGrow model is capable to predict a realistic spatial pattern of the rill network in response to a given rainfall event (Favis-Mortlock, 1996). The erosion model series of RillGrow mainly expresses the eroding hillslopes on a small scale as a self-organized dynamical system producing a rill network (Horton, 1945). Digital elevation models of the hillslopes used as an input to the RillGrow simulates the rill network as a whole system which later on is compared with the field and laboratory experiments for validation (Favis-Mortlock et al., 1998). A logistic S-Curve, the relationship between flow energy and sediment load, is considered to estimate erosion resulting from the surface flow. Hillslope micro-topography could be responsible for the observed vitality of rill competition and spatial pattern of overland flow initiating lowering of the surface. Such modifications change the path of the soil erosion process as it creates its own surface (Zobeck and Onstad, 1987). This simple relationship develops a complex rill network. However, this simplicity results in limited model computational abilities as the flow process and erosion have to be predicted on a microscale. Also, model data requirement creates issues. These limitations make this model impractical for real-world erosion simulations. Simulations have an immense demand of computation time if the area is larger than the hillslope plot or laboratory experiment (Meyer and Wischmeier, 1969). There are a few articles on GIS integration with the RillGrow model in the latest versions. That needs to be worked out to improve the workability of the RillGrow model in the future.

3.3.6. Erosion-Productivity Impact Calculator, EPIC

EPIC is a detailed model developed to simulate, simultaneously and realistically, the physical processes involved by developing the relationship between soil losses and soil productivity. EPIC mainly uses climate, land cover, tillage, and soil characteristics as in-put variables. Many applications of EPIC have been studied in the United States and worldwide under varying environmental conditions, for example, climate change effects on crop yield and soil erosion (Parsons et al., 1995; Parton et al., 2015), wind erosion (Potter and Williams, 1994), irrigation impacts on crop yields (Cabelguenne et al., 1997, 1995), assessment of soil temperature (Roloff et al., 1998), and soil carbon sequestration as a function of management and cropping systems (Apezteguía et al., 2009; Lee et al., 1993). The model has been extensively tested in many ways. The EPIC model has nine major components, namely, weather, nutrients, plant growth, soil temperature, hydrology, environment, and economics. Each component was tested (J. R. Williams et al., 1984; Knisel, 1982; Nicks and Harp, 1980; Smith et al., 1985; Williams et al., 1985, 1983) and the results were found to be acceptable and reliable. (Williams, 1990) proposes that the EPIC model works more efficiently over small areal extent (generally ~ 1 ha) because management practices and soils are considered homogenous. However, the model can consider all kinds of soil properties. Traditionally, EPIC is site-specific, but when integrated with GIS tools, regional crop growth and yield can be simulated (e.g. the G-EPIC version (Williams, 1990). GIS is used to produce model inputs for DEM, land use/land cover, and soil maps. Due to EPIC's extensive testing and high integration with GIS, its application has been increased and has become famous among scientists.

3.3.7. Chemicals, Runoff, and Erosion from Agricultural Management System, CREAMS

The Chemicals, Runoff, and Erosion from Agricultural Management System model was developed in the United States (Knisel and Nicks, 1981). CREAMS is a physical, daily-based dynamic model that simulates runoff, erosion, and sediment yield, having a capacity for assessment of nutrient loss and chemicals from agricultural lands suitable at field scale (Williams et al., 1985). Hydrology is one of the components of CREAMS that is the principal element to simulate soil erosion neglecting the deep percolation. With the daily rainfall data, the SCS curve number is used to estimate surface runoff (Mockus, 1972). These component results provide the in-put to other components of CREAMS to estimate nutrient and chemical losses. The erosion component in CREAMS uses USLE along with sediment transport for overland flows. Studies show that the CREAMS model performs better for field-scale but it can be applied to larger-scales (~400ha) (Merritt et al., 2003). This may be due to the fact that the model assumes uniform topography and land use and it does not consider temporal variations in soil erodibility which is highly unrealistic in the real world. Moreover, (Govers and Loch, 1993) observed that dynamic simulation of water erosion may limit the accuracy of estimations because of their extensive dependents on the validated input data. However, such limits can be reduced using physically based models rather than empirical models such as CREAMS.

3.3.8. The Griffith University Erosion System Template, GUEST

The Griffith University Erosion System Template (Hairsine and Rose, 1991) is a physically based steady-state sediment flux model developed to simulate single events of erosion resulting in temporal variations in sediment yields at a plot scale. The model uses hydrological and surface characteristics of uniform slope and relates rainfall-runoff rates to predict the yield of eroded sediments (R. K. Misra and Rose, 1996). The model algorithms explaining erosion, transport, and sediment yield are based on single rainfall events at the plot scale. GUEST considers the erosion process to mainly be due to rainfall impact and the effect of overland flow generated shear stresses exerted on soil, making GUEST a comparatively complex process-based model which requires a large number of input data. (Huang et al., 2007) noted the low ac-curacy in predicted soil erosion by surface runoff when applied to the catchment scale and that it was limited by the extent of data required at the plot scale.

3.3.9. The Productivity, Erosion and Runoff, Functions to Evaluate Conservation Techniques, PERFECT

The PERFECT model (Littleboy et al., 1992c) was developed by the Queensland Department of Primary Industries and the QDPI/CSIRO Agricultural Production System Research Unit in Australia. This model was developed to integrate with other physically based models such as CREAMS for studying the impact of soil management factors i.e., field preparation practices and soil conservation techniques. CREAMS excludes the land cover variations caused by tillage practices to estimate surface runoff. PERFECT model considers management strategies to predict surface runoff, erosion (MUSLE), and crop production on daily time steps at the field scale. As other models can be incorporated into the PERFECT model, it is a mix of conceptual, empirical, and physically based models.

(Littleboy et al., 1992a) suggested that the PERFECT model is more accurate than CREAMS for estimating runoff, accounting for 77-89 % of the variation in measured (Gaiser et al., 2013a) daily runoff volume. However, this model does not consider the impact of rainfall intensity thus resulting into over/underestimation of soil erosion based on a single rainfall event. Sediment and nutrient components may be added for water quality modeling that may provide an advantage with crop cover data and management components where it is needed.

4. Discussion

4.1. Selection criteria for soil erosion models

Each soil erosion model has its predictive capabilities and modeling processes and its applicability depends on its intended use, available input and calibration data, temporal and spatial scale, and required accuracies. Based on the review work, the selection of a suitable model for a distinct purpose at the field-scale should be guided by the following criteria. 1) Problem recognition: Define the problem statement in a clear way to achieve a maximum match between the problem to be solved and the model objectives. 2) Spatial scale: the next criteria is to decide whether the model is compatible with the plot or field scale. 3) Data availability: make a list of required input data (topography, climate, field investigations) and their availability. 4) Temporal scales to be considered (event-based or continuous) 5) Elements to be assessed; decide which elements of the catchment are to be modeled i.e., overland erosion and sedimentation, hillslope erosion, or channel/stream erosion and sedimentation. 6) Model sensitivity; the uncertainties within input data should be identified that may impact the reliability of the simulated results before the model evaluation. 7) Model validation; simulation results must be compared with field observations that may also use for model calibration before the simulation process.

4.2. Capabilities and limitations of field scale models

Soil erosion models are bound to have certain strengths and limitations depending on their different development objectives and often specific environmental processes and conditions. Most of the available soil erosion models have been developed mainly for larger scales (basin or watershed) where spatial variations in soil conditions (soil erodibility, soil cover, slope, and tillage practices) and hydrological conditions (surface runoff, in-filtration rate, and rainfall intensity) are significant compared to those at small scales (field or plot). Individual hydro-geomorphological processes and vegetation impact differently on soil erosion process across various scales. Slope arguably is one of the major factors in the erosion process. For models such as EPIC, WEPP, CREAMS, and GLEAMS that use USLE to reflect the effect of slope length on soil erosion, the major problem (Table 2.6) is the suitable selection of slope segments in fields with complex topography where slope characteristics may vary drastically. EUROSEM is a model that uses a dynamic mass balance equation to simulate the erosion process at a field scale for agricultural lands. EPIC predicts soil losses from rill and inter-rill areas all together whereas EU-ROSEM, WEPP, and GLEAMS estimate each separately.

The assumptions regarding the soil erodibility and tillage formation have a great influence on predicting the volume and direction of surface runoff and subsequently soil losses. TCRP is a 2-D empirical model, which simulates runoff patterns with the flow along the direction of plow lines in tilled fields assuming runoff direction always in direction of tillage (Table 2.6). TCRP can consider both tillage-controlled runoff patterns and topography-controlled runoff patterns. EPIC runoff factor considers ridge heights between furrows to estimate total runoff. EUROSEM and WEPP coupled with MIKE SHE/MIKE 11 can simulate daily soil losses considering different conservation practices at the field scale.

Although the above mentioned problems are significant, calibration of field scale models in fields characterized by spatial heterogeneity of topography and soil is more ac-curate than for larger catchment areas. Furthermore, the accuracy of the simulation of erosion rates depends on the spatial dimension taken into account, i.e. whether processes are simulated at the soil profile scale (1D, point based assuming a field with homogeneous soil and terrain conditions) and/or spatially distributed method (2D/3D) (Table 2.6). The quality and accuracy of the calibration of the erosion processes in heterogeneous fields should increase with the dimension that is considered. However, a major bottleneck for the multi-dimensional models is the availability and accuracy of soil information. On the other hand, the accuracy and availability of topographic information has considerably improved in the last decade (e.g. radar and laser based sensors carried by UAV or air-planes).

4.3. Model comparison with respect to simulating soil erosion in complex cropping systems

Conservation practices like strip and patch cropping or agroforestry systems are important management options to improve floristic and faunistic diversity in intensively used agricultural landscapes. Tools are required to predict the impacts of such diverse cropping systems on soil erosion processes. The Water Erosion Prediction Project (WEPP) for the intercropping system, Water Nutrient and Light Capture in Agroforestry Systems (WaNuLCAS), and Agricultural Production Simulation (APSIM) models are capable of simulating soil erosion in conventional and complex cropping systems at the field scale. WaNuLCAS represents dynamic processes in the spatial domain. It was designed to simulate Tree-Soil-Crop interactions under a wide range of agroforestry systems. It uses the Rose equation to simulate the erosion process in a simplified 2D approach. However, this component of WaNuLCAS has not been tested extensively and requires further investigation. APSIM offers many modules (generally categorized as biological and environ-mental modules). The erosion model is capable of simulating the impact of erosion on the soil profile as soil loss occurs under different management practice options such as strip cropping and alley cropping systems, but it considers only one dimension in the field. Notably, APSIM has high input demand, most of which requires extensive field investigations.

Another important aspect is the translation of rainfall to runoff under varying canopy interception in complex cropping systems. A realistic representation of the role of canopy cover in rainfall-runoff modeling is essential when predicting sediment transport in heterogeneous fields along hillslopes. A few models such as EPIC, WEPP, EUROSEM, CREAMS, SCUAF, and WaNuLCAS account for the intercepted rainfall to estimate total runoff (Table 2.6). However, to this date, there is no cropping model available at the field scale that considers the impact of cropping systems like strip cropping and patch crop-ping and their complex canopy arrangements affecting runoff induced soil erosion processes. EPIC, WEPP, EUROSEM, and CREAMS models may have the capabilities to model complex variations in cropping systems when integrated with GIS (Knisel, 1982; Pumijumnong and Arunrat, 2012; Renschler and Harbor, 2002).

The review suggests that further studies have to be conducted to develop tools that facilitate the integration of modeling components to lower the complexities of source codes and to further improve existing models or develop new models that represent soil erosion processes under complex cultivation patterns on the same field. Modeling capabilities should be improved and tested with respect to the soil erosion process in strip and patch cropping systems as well as agroforestry systems. Existing agroforestry models must be improved to incorporate erosion processes in fields with high spatial heterogeneity with respect to soil properties, slope inclination, and length, preferably considering three dimensions. Such new developments might also support upscaling of soil erosion processes to larger spatial scales (watershed to basin scale).

4.4. Summary and Conclusions

Soil erosion processes strongly differ with spatial and temporal scales and environ-mental conditions. Thus, a large number of models have been developed that differ in terms of the processes considered, temporal and spatial application scale, capabilities, and limitations. Based on their processing concepts, these models were classified into three categories 1) Empirical models, 2) Conceptual models, 3) Physically based models.

Most of the empirical models use the universal soil loss equation (USLE) and its derivates RUSLE and MUSLE. Though these equations have been developed using data obtained in the United States, these equations are applied worldwide for soil loss estimations. Under variable conditions of spatial soil characteristics and insufficient meteorological networks, empirical models are less complex to operate which makes them a potential choice for predicting soil erosion. Hence, the empirical models are more likely to be used with limited availability of input data. Contrary to that, physically based models provide a physical description of the erosion process. These models are comparatively complex and less user-friendly because of their detailed depictions of processes and large data requirements. However, physically based models are more capable when performing event-based simulations. Conceptual models typically have been developed for catchment and larger scales, requiring a general description of the catchment and involved soil erosion processes, without describing the details of their interactions that would require big data sets of temporal and spatially distributed catchment details. However, there is currently no model available to represent soil erosion processes in more complex cropping at the field scale like strip and patch cropping or alley cropping systems. There are some crop models available to simulate alley cropping systems such as APSIM or WaNuLCAS, with soil erosion components. However, these models have not been tested and validated for erosion estimation and its impacts on subsequent crop yield.

The literature review indicated that most of the models developed for large agriculture catchments using equations developed under specific conditions require site-specific calibration before simulation. Models designed for small time steps perform better than continuous scale modeling. Similarly, calibration at a field or smaller scale, where spatial topographic and soil variations on erosion process greatly affect the simulation, is more accurate than that of larger catchment areas. It is worth indicating that some models such as EPIC, PERFECT, GUEST, EPM, TCRP, APSIM, and CREAMS were developed for soil erosion assessment at plot/field scale at daily time steps. Limited workability of these models was found for sediment transport, sediment deposit, and sediment yield. Models such as EPIC, WEPP, EUROSEM, CREAMS, SCUAF, and WaNuLCAS have the capability to account for rainfall interception but further improvements are required to deal with complex cropping systems.

5. A way forward

Soil erosion modeling at a field scale is now facilitated by very high spatial and temporal resolution remote sensing (RS) data, which allow for frequent estimation of characteristics of crop cover and topsoil characteristics at the field scale. RS data can be used as both model input (e.g., micro topography, within-field variability of oil and plant characteristics) and validation data (e.g. based on LiDAR data (Sankey et al., 2021)). In order to benefit from RS data flexible data assimilation methods have to be developed for physically based models whereas their integration into empirical and conceptual models is relatively straight-forward. At larger scales, EU wide surveys of topsoil (LUCAS) and Land Use/Cover Area (CORINE) are carried out every three years. Such harmonized open-access data are currently not fully exploited by soil erosion models and might be used as input data for urgently needed model inter comparisons in order to increase our confidence in predicted erosion rates. Further, with increased concerns on future soil erosion rates under climate change (Eekhout et al., 2021) the systematic evaluation of soil erosion models and ensemble soil erosion models (Borrelli et al., 2020) using harmonized data sets might be used to support land use policies.

Models such as EPIC, WEPP, EUROSEM, and CREAMS may have the capabilities to model complex cropping systems such as strip cropping and patch cropping, their spatial arrangements, and their impact on soil erosion when integrated with GIS or into flexible modeling frameworks. Integration or coupling of soil erosion components in a modeling framework for dynamic simulation can provide an alternative to conventional erosion modeling at a field scale and may facilitate upscaling to larger scales.

In the context of sustainable agriculture, there has been an increasing interest in the application of novel crop arrangements within a field (OECD, 2003) in recent years. Since these novel field designs, e.g. alley cropping or strip cropping, are assumed to support the delivery of ecosystem services, such as a reduction of soil erosion, there is a need to quantify such effects. A larger number of case studies, based on the combined use of high-resolution RS data with soil erosion models, are required in order to highlight the potential of novel field designs to reduce the risk of soil erosion and to support corresponding changes in agricultural policy. An important conclusion of this review is, there-fore, the need for future research and development with respect to modeling soil erosion under complex spatial cultivation patterns.

The present study provides a clear description of individual models to sort out which model fits which conditions and problems identified and leads to clear guidelines to select the appropriate model. Future studies need to integrate modeling working components to enhance the strength of models. There should be models developed for soil erosion process in agroforestry systems and existing agroforestry models must be improved to incorporate erosion process and yields. This review emphasizes enhancing the quality of the modeling output and should have additional components to enhance their applicability in most environmental and management conditions.

Chapter 3

Using the Taguchi experimental design for assessing within-field variability of surface run-off and soil erosion risk

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1. Introduction

Soil erosion by water has become a great concern all over the world (Keating et al., 2003; Krysanova et al., 2007). Soil erosion has significant impacts on environmental sustainability by adversely influencing agricultural production, water quality, and natural resources conservation (Issaka and Ashraf, 2017). It reduces the fertile soil depth and crop available soil moisture by the removal of essential nutrients and soil organic matter (SOM) and hence reducing the productivity of the soil (Jahun et al., 2015). Soil erosion by water is a form of land degradation resulting from multiple factors with complex interactions. Among others, these factors are rainfall intensity, runoff, small-scale soil heterogeneity in the vertical and horizontal direction, topography, and temporal variability of crop conditions (Václavík et al., 2013). Affected by heterogeneous environmental and field conditions, soil erosion involves complex processes that can strongly vary within single fields, in particular in undulated areas. (Cerdan et al., 2010). Therefore, identifying and categorizing the main causes of soil erosion at the field scale based on observations with a high spatial resolution for quantitatively assessing the spatial and temporal variability of soil erosion patterns are of great importance. Such information can provide support for decision-making for improved sub-field management and for farmers to avoid the degradation of fertile soils and for maintaining or enhancing crop productivity.

Numerous experimental and modeling studies have been conducted using approaches ranging from analytical to empirical techniques to gain a better understanding of runoff and soil erosion processes (Raza et al., 2021) and their potential outcomes (organic carbon and nitrogen losses, soil depth reduction, etc.,) under heterogeneous field conditions (Aga et al., 2020; Eslamian, 2014; J. R. Williams et al., 1984; Knisel and Nicks, 1981; Syvitski and Kettner, 2008; Viney and Sivapalan, 1999). Individual hydro-geomorphological processes and vegetation dynamics affect the soil erosion process differently depending on the scale (Aga et al., 2020; Nearing et al., 1999; Panagos and Katsoyiannis, 2019). In particular, soil physical properties such as soil structure, texture, bulk density, compaction, and soil thickness influence the erosion pattern and thus rate and magnitude of erosion (Ouyang et al., 2018; Ramezanpour et al., 2010). Other driving factors are the topography (i.e., slope gradient, slope length) and ground cover, which modify the physical forces and greatly impact hydrological processes (Liu and Singh, 2004). The amount, intensity, and frequency of precipitation are critical meteorological factors for surface runoff generation and soil erosion.

A few authors investigated the interactive impact of environmental and soil conditions on soil erosion. (Guidry et al., 2006; Sepaskhah and Bazrafshan-Jahromi, 2006) investigated the runoff and soil erosion under rainfall, varying slope, and soil factors, and found that the potentialities of both surface runoff and sediment yield varied with the level of rainfall erosivity but the impact differed among soil textures and slopes, indicating diverse nonlinearities of rainfall-runoff-soil factors-erosion relationships and their complex interaction. (Zambon et al., 2021) studied the dependency of soil erosion on soil surface conditions (seal formation) and soil types under controlled rainfall intensities. Under the same initial surface conditions, the erosion development for increasing rainfall intensity was almost consistent. (Warrington et al., 1989) noticed that increasing slope inclination tends to increase erosion, whereas removing surface crusts and increasing permeability rate led to decreasing surface runoff. (Gross et al., 1991) concluded that even low density vegetation coverage noticeably decreases the sediment yield with increasing rainfall intensities. However, different studies yield a different representation of erosion processes Differences in the results of the studies are mainly caused by the particular experimental conditions (selection of factors) and set-ups which affected the output. To date, there are a few attempts made to study the impact of multiple environmental and in-field factors to predict sediment yield and runoff, including, in some cases, carbon, and nitrogen losses under natural conditions (Anh et al., 2014; Li et al., 2017; J. H. Zhang et al., 2015). Most of these studies consider only one (Cerdà et al., 2021; Dunjó et al., 2004) or two (Ouyang et al., 2018; Ramos et al., 2019) factors to explain the erosion process and ignore the complex interaction of potential factors and specifically their in-field variability that may strongly affect the sediment yield and surface runoff. Most of these studies used defined rainfall intensities at plot scales to investigate soil erosion using a rainfall simulator.

Rainfall simulators and soil erosion plots are two widely used research facilities to assess and quantify the processes of soil erosion and sediment transport in overland flow (Sharpley and Kleinman, 2003). Different types of rainfall simulators with their specifications and sizes being optimized for specific pedo-climatic zones, topographies and land uses have been successfully applied in several field experiments (Barthès and Roose, 2002; Duiker et al., 2001; Fernández-Gálvez et al., 2008; Guidry et al., 2006; Lasanta et al., 2000; M. Sheklabadi et al., 2012; Sepaskhah and Bazrafshan-Jahromi, 2006; Srinivasan et al., 2007). However, many of these studies used standard plot sizes under controlled conditions (Albaladejo Montoro and Stocking, 1989; Raza et al., 2021; Renard et al., 1991) and with rainfall intensities far higher than the threshold for soil detachment thus neglecting the interactions of modulated intensities and soil characteristics that can drive fine-scale spatial soil erosion processes (Kusumandari et al., 2021; Poulenard et al., 2001). In summary, there is still a lack of knowledge on the interactive effects of multiple factors and their potential levels on soil erosion processes under natural conditions that explicitly consider sub-field scale spatio-temporal dynamics. The quantitative knowledge is however of great importance for agricultural fields where management activities can lead to changes in the vulnerability of soils to erosion. Spatially explicit knowledge will help to understand within-field dynamics of erosion and sedimentation and greatly support precision agriculture by developing physical-based on empirical-based models. . Further, it provides quantitative validation data for high-resolution remote sensing data (such as unmanned aerial vehicle (UAV)-based Lidar measurements).

Most of the previous studies were conducted under controlled conditions with a limited number of factors, factor levels, and their interactions (Liu et al., 2019; Rieke-Zapp and Nearing, 2005; Sadeghi et al., 2017; Yusuf et al., 2016). Observing multiple factors and their complex interactions requires establishing several field experiments to disentangle their effects on spatial variation in soil erosion. Therefore, these studies used full factorial experimental designs to investigate the magnitude of the effects of factors on soil erosion that require a large sample size because it increases exponentially when all combinations of factors, factor levels, and interactions are considered (L. D. Meyer, 1981; Li et al., 2019; Meyer and Harmon, 1989). These designs are not applicable when the number of experimental runs is limited due to their cost- and labor intensity. To handle this challenge, the Taguchi method can be applied to any experimental study where the effect of up to ~30 factors on processes is studied while labor and cost intensity are minimized without lowering the quality of outputs (Taguchi, 1986). The Taguchi method is a type of general fractional factorial design, based on a selected number of factors and factor levels to identify the least number of experiments to be performed without compromising the overall output (Taguchi, 1987, 1986). So far, in an agricultural context, the Taguchi design mainly has been used for investigating the impact of fertilizer rates and plant density on cotton yields (Awty-Carroll et al., 2020; Chou et al., 2010; Ruchika Deo et al., 2007; Sivaiah & Chakradhar, 2019b). Further, it has been successfully applied to study soil erosion processes (Sadeghi et al. 2012, Mhaske et al. 2019) and results indicate similar performance compared with full factorial designs (Zhang et al. 2015, Zhang et al. 2021) and response surface methods (Moosavi & Sadeghi. 2021(F. Zhang et al., 2015)). While providing evidence for the suitability of the design to study the effect of multiple factors on soil erosion, these studies only used a limited number of factors and their interactions. Further, runoff volume and resulting nutrient losses such as organic carbon and nitrogen from the field, which are critical variables for sustainable agriculture, were not investigated.

Encouraged by the successful application of this design in the studies mentioned above, we here use the Taguchi design to study fine-scale spatio-temporal dynamics of soil erosion processes (surface runoff, sediment yield, carbon and nitrogen losses) as affected by multiple factors at an agricultural field located in Western Europe under temperate climate conditions. More specifically, the objectives of this study are to

i. Investigate the within-field variability of the effects of the interaction between soil characteristics (soil organic matter (SOM), soil texture), topography (slope), rainfall intensity, and soil cover (field conditions) on soil erosion, surface runoff, carbon and nitrogen losses
ii. Quantify the percentage contribution of each of these five factors to soil erosion, surface runoff, carbon and nitrogen losses
iii. Develop empirical models to predict local runoff, sediment yield, carbon and nitrogen losses
iv. Identify erosion risk and sediment yield zones within the field

2. Methodology

2.1. Study area

The study was conducted on an agricultural field site located in the Löwenberger Land municipality, in the north of the federal state of Brandenburg, Germany (33U 374170E 5866893N) (Fig. 3.1). Brandenburg lies in the temperate, continental climate zone with mean annual temperatures between 7.8 °C and 9.5 °C and mean annual precipitation of ~ 600 mm (German Weather Service 2020, Ihinegbu & Ogunwumi, 2021). The research field comprises ~ 6.25 ha (Fig. 3.1). Terrain height averages around 51.5 to 57.5 m a.s.l. with north east facing gentle slope (Fig. 3.2). The soil was classified as Ferric Luvisol at up slopes (WRB, 2007) and in the marginal areas of the depression as Gley-Kolluvisol (Gleyic Anthrosol).

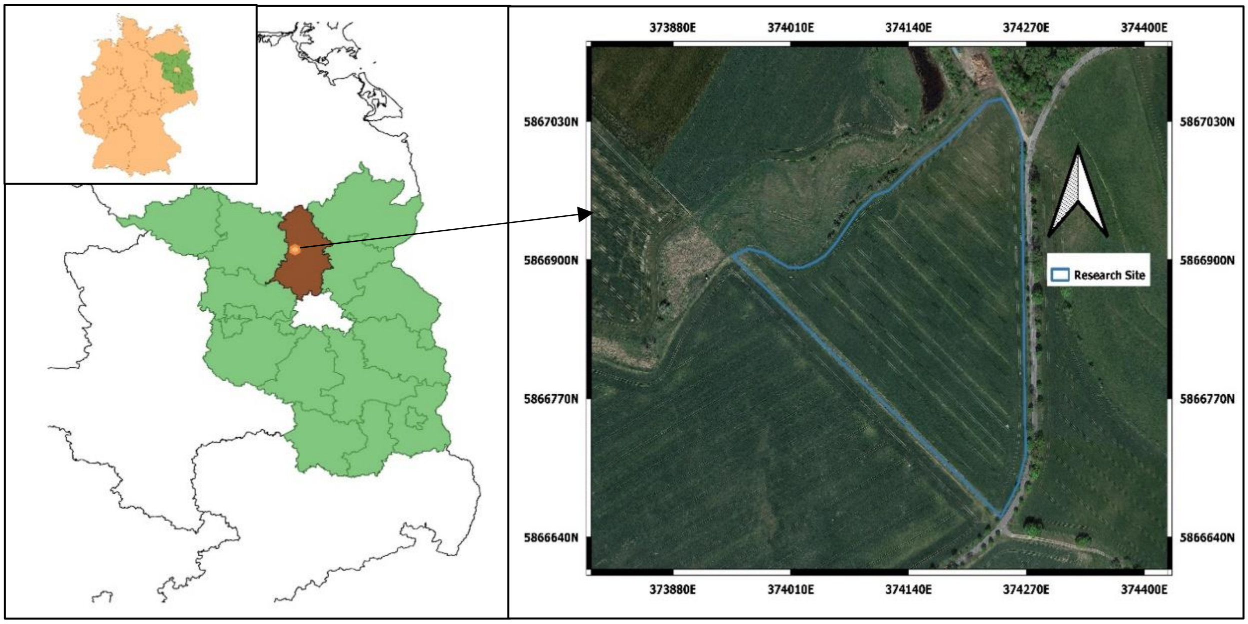


Fig. 3. 1: Location of the study area (left) and an aerial image of the research field (May 8th, 2020, Google Earth)

2.2. Soil sampling

To characterize the spatial heterogeneity of soil characteristics soil augers (100 cm depth) were obtained from 87 different locations within the field (Fig. 3.2) in December 2019. At selected points, soil samples were analyzed for soil texture (proportion of silt, sand, and clay fractions) and SOM content, and the depth from the soil surface to a loamy layer. In soils derived from glacial deposits, the thickness of the sandy topsoil layers that are followed by a loamy layer, restricting vertical water movement compared to the sandy topsoil, is considered to increase the risk of water ponding at the soil surface and hence the risk of surface runoff and erosion. Samples were air-dried and sieved through a 2 mm mesh. Particle size distribution was determined with the Pipett method after SOM and carbonate destruction. Soil texture varied from silty loam to silt and medium sand according to the German soil taxonomy. According to Hofmann et al. (2016) and the soil taxation values in the German field cadastre of the state of Brandenburg (BB ATKIS), however, the topsoil is dominated by loamy sand.

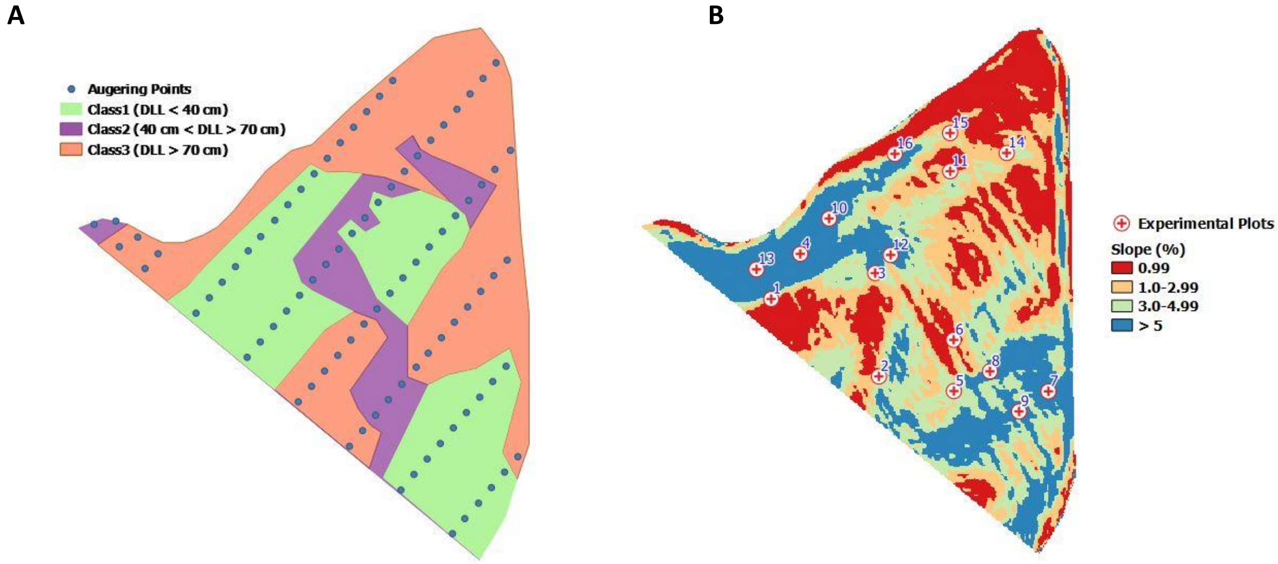


Fig. 3. 2: Study site with soil augering points (A) and the locations of the rainfall simulation experimental plots (B, Numbers 1 to 16)

2.3. Experimental design

In contrast to classical statistical designs the "Taguchi design" is a type of general fractional factorial design, based on a selected number of factors and factor levels to identify the least number of experiments to be performed (Taguchi, 1987, 1986). The main factors and interactions that are most likely to be significant and the levels at which they are varied have to be defined in advance. Based on this knowledge Taguchi orthogonal arrays are selected with the choice depending on the tradeoff between time, resources, and quality of outputs (Medan et al., 2017; Rafidah et al., 2014; Woll & Burkhard, 2005). Subsequently to the experimental runs, the effect of each variable can be studied based on the signal-to-noise ratio (SN) (i.e., maximizing or minimizing SN ratios).

The Taguchi method systematically yields the best possible combination of factors and their levels to produce quality output at lower experimental cost and time. Based on the literature review (Chmelová and Šarapatka, 2002; P.U. et al., 2017; A. Pandey et al., 2007; Raza et al., 2021), For this study, five factors were selected: Sum of the percentage of silt and soil organic matter (SiltOM), vegetation cover (VC), slope steepness (SS), rainfall intensity (RI), and depth to loamy layer (DLL). For each factor, four levels are considered (Table 3.1). The ranges of these levels are based on soil surveys, site-specific scheduling of crop residue management (affecting vegetation cover), and the field topography derived from 2008 Lidar data with 1m spatial resolution (https://geobroker.geobasis-bb.de). The selection of rainfall intensity levels is based on an analysis of 10-minute precipitation data provided by the German Weather Service for a nearby meteorological station (Brandenburg weather station (ID # 3552)) and adjusted to the capability and sensitivity of the mobile rainfall simulator (described below).

Table 3. 1. Experimental factors and their levels

Factor	Description	Unit	Level 1	Level 2	Level 3	Level 4
1	(SiltOM)*	%	> 20	18 - 20	16 - 18	< 16
2	vegetation cover	%	1 - 5 (C)	0 (B)	10 - 15 (E)	> 15 (L)
3	Slope steepness	%	< 1	1-3	3-5	> 5
4	Rainfall intensity	mm min^{-1}	< 2.5	2.7 - 3.3	3.4 - 4	> 4
5	Depth to loamy layer	cm	< 40	40 - 55	55 - 70	> 70

*the % of SiltOM decreases from level 1 to level 4, decided based on laboratory soil texture analysis. C, B, E, and L represent field conditions as cultivation, seedbed preparation, plant emergence, and Leaf development stage (3 Leaves unfold) respectively.

Due to the number of factors (5) and levels (4) as defined in Table 3.1, the orthogonal array L_{16} (4^5) for the Taguchi DOE was selected consisting of 16 experiments (factor combinations) (Table 3.2).

Table 3. 2. Taguchi fractional factorial design L16 (45) used in this study

Factors \ Plot ID	Combination of levels					SiltOM (%)	Vegetation cover (%)	Slope steepness (%)	Rainfall intensity (mm min^{-1})	Depth to loamy layer (cm)
	1	**2**	**3**	**4**	**5**					
1	1	1	1	1	1	>20	1-5	<1	<2.5	<40
2	1	2	2	2	2	>20	0	1-3	2.7-3.3	40-55
3	1	3	3	3	3	>20	10-15	3-5	3.4-4	55-70
4	1	4	4	4	4	>20	>15	>5	>4	>70
5	2	1	2	3	4	18-20	1-5	1-3	3.4-4	>70
6	2	2	1	4	3	18-20	0	<1	>4	55-70
7	2	3	4	1	2	18-20	10-15	>5	<2.5	40-55
8	2	4	3	2	1	18-20	>15	3-5	2.7-3.3	<40
9	3	1	3	4	2	16-18	1-5	3-5	>4	40-55
10	3	2	4	3	1	16-18	0	>5	3.4-4	<40
11	3	3	1	2	4	16-18	10-15	<1	2.7-3.3	>70
12	3	4	2	1	3	16-18	>15	1-3	<2.5	55-70
13	4	1	4	2	3	<16	1-5	>5	2.7-3.3	55-70
14	4	2	3	1	4	<16	0	3-5	<2.5	>70
15	4	3	2	4	1	<16	10-15	1-3	>4	<40
16	4	4	1	3	2	<16	>15	<1	3.4-4	40-55

2.4. Plot selection

To select plot locations for experimental runs covering each of the 16 factorial combinations (Table 3.2), field maps on the depth to a loamy layer, slope inclination, and the sum of silt and OM were prepared, using SAGA within QGIS 3.16 (Fig. 3.3). Data on the depth to a loamy layer was derived from field surveys. Point data were spatially interpolated using ordinary kriging in SAGA. The topography was derived from 2008 LiDAR imagery (https://geobroker.geobasis-bb.de). Subsequently, map overlays were used to identify 16 plot locations. The 16 locations were considered to be well distributed in the research site (Fig. 3.2). At each location, rainfall simulator experiments were carried out at the respective intensity levels with 4 repetitions. To integrate the factors "vegetation cover", simulations were performed on multiple dates with vegetation cover ranging from 0% (seedbed preparation), over 5% (cultivation) and 10% (crop emergence, DAS: 20) to >15% (leaf development stage 3, DAS: 204) (Table 3.3).

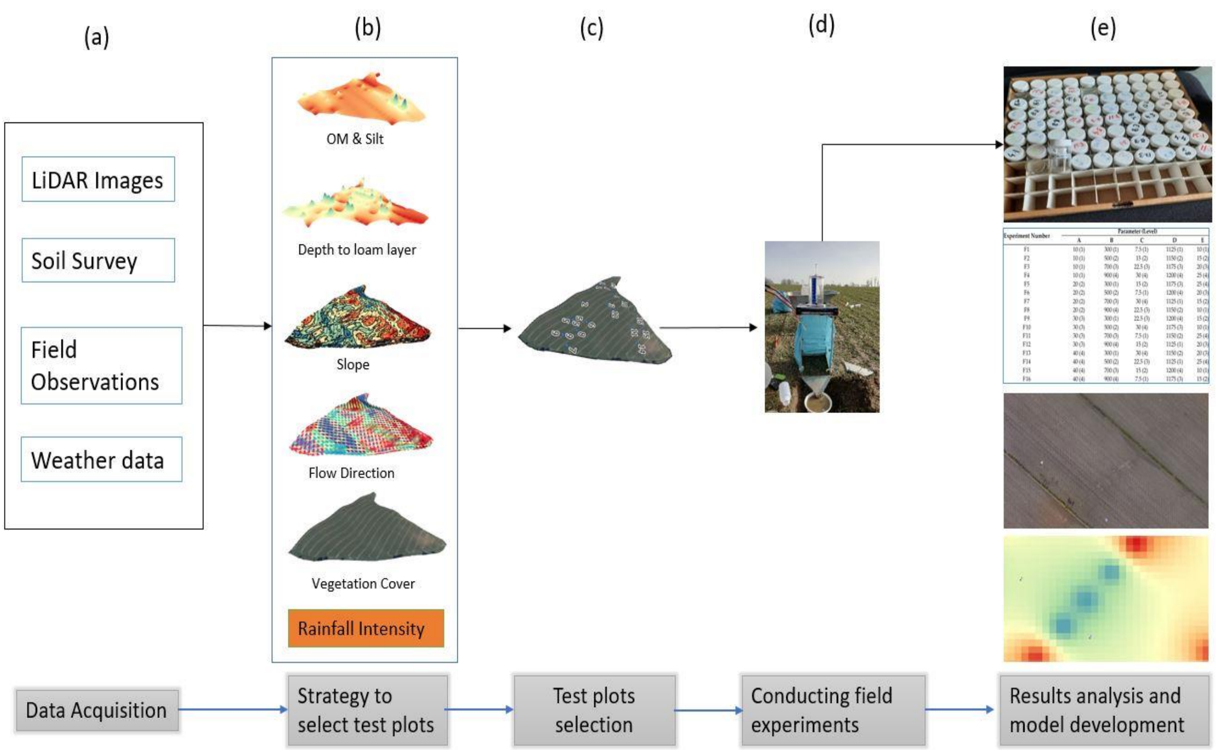


Fig. 3. 3: Schematic diagram of the workflow for the rainfall simulation experiment: (a) Preprocessing of soil samples and remote sensing data (b) Preparing within-field factor levels for the Taguchi design (c) Selecting the locations of experimental plots (d) collecting sediments and runoff (e) Filtering and weighing sediment samples, runoff and CN concentration in sediments

2.5. Rainfall simulator

In this study, in order to generate targeted levels of rainfall intensity (Table 3.2), the portable non-pressurized rainfall simulator (Kamphorst, 1987) was used (Fig. 3.3d). The simulator was produced by Eijkelkamp (Eijkelkamp Agrisearch Equipment, Netherlands) and the design is owned by Wageningen University Research Centre. The ground coverage area is 0.0625 m^2 enclosed from three sides with stainless steel frame. The basic unit of the simulator consists of two Plexiglas containers connected with the frame. The upper container has a calibrated cylindrical reservoir having a capacity of 2300 ml. The lower container has 49 capillaries with a diameter of 0.6 mm. The basic unit is supported with four adjustable legs, 0.4 m average in height, on various slopes. Rainfall intensity is controlled by varying the atmospheric pressure inside the basic unit through an adjustable aeration pipe attached to the upper container. Fig. 3.3d illustrates the operation of the rainfall simulator in the field. Before the beginning of the experiments, the rainfall simulator was calibrated in order to generate the four different rainfall intensities (Table 3.2) (Kamphorst, 1987; "Rainfall simulator - Field measurement equipment | Eijkelkamp," 2018). Each experiment was carried out for the duration of 8 minutes keeping in view the storage capacity of the reservoir and rainfall intensity levels. However, for the rainfall simulator, it is recommended to use it at the wettest season i.e., soil moisture content near to field capacity, when the soil surface is most vulnerable to erosion. For that purpose, a pre-wetting of the plot was carried out in the dry season. The water for pre-wetting is carefully applied through a plastic container with a perforated lid on it to avoid splash and runoff.

2.6. Sample preparation

The runoff from each plot and repetition and the corresponding sediment yields were collected in a 2L plastic bucket installed at the downslope end of the stainless steel frame of the simulator. The samples were thoroughly mixed by stirring before transferring them into plastic bottles. The volume of samples (runoff + sediment) was determined using glass flasks in the laboratory followed by wet sieving through a sieve with a mesh size of 2 mm. The samples were then placed in the oven at 60 ^{o}C for drying the dried samples and were later weighted to determine the sediment yield. There were no stones > 2 mm collected in any of the samples. A pycnometer with distilled water was used to determine the volume of sediments collected from each experimental plot (Benjeddou et al., 2017; Heiskanen, 2008). Surface runoff volume was calculated by subtracting the sediment volume from the total sample volume collected in the field. The sediment samples were then dried at 60 ºC till samples were fully dried to prepare them for carbon and nitrogen (CN) analysis. The dried samples were transferred then into separate glass scintillation vials and analyzed for CN content by instantaneous oxidation of the sample via combustion with oxygen at an approximate temperature of 1020° C using an Elemental Analyzer Euro EA 3000 (EuroVector - RK Tech Ltd., Pavia)

2.7. Statistical analysis

In Minitab 17.0 software tool, signal-to-noise ratio analyses (SN) were used for the evaluation of experiment results (Chou et al., 2010; Sivaiah and Chakradhar, 2019). Three types of SN ratios are used (1) Nominal is better, (2) Higher is better, (3) Lower is better. Because the objective of this study is to identify the areas with the highest risk of erosion, "the higher the better (HB)" approach was used. The following equation was used to calculate the SN-ratio:

$$\frac{S}{N_s} = -10 * \log\left(\frac{1}{n}\sum\frac{1}{y^2}\right) \tag{1}$$

where, *n* represents the number of repetitions at each rainfall simulation plot, and *y* represents the studied variable. Here, *y* is sediment yield, runoff, nitrogen, or carbon content in the sediments from each experimental plot.

The statistical approach of analysis of mean (ANOM) was used to derive optimal conditions (Parr and Taguchi, 1989). ANOM is a graphical method for multiple group comparisons with an overall mean ("grand mean"). The mean $\frac{S}{Ns}$ ratio of each factor *I* at a specific level *i* (Eqn. 2) was determined using the following equation:

$$M\,{}^{Level}_{Factor} = \frac{1}{n_{Ii}}\sum_{j=1}^{n_{Ii}}\left[\left(\frac{S}{Ns}\right)^{level=i}_{Factor=I}\right]_j \tag{2}$$

In equation (2), n_{Ii} is the number of occurrences of factor *I* in level *i*. $\frac{S}{Ns}$ response figures and tables were obtained, and optimum conditions were established for each concerning output. J?

In addition, an analysis of variance (ANOVA) was used to investigate the influence of individual factors on sediment yield, runoff, and CN content (Cox et al., 2008). The percentage contribution of each experimental factor to the four output variables was estimated using the following equation:

$$\rho_F = \frac{SS_F - (DOF_F V_{ER})}{SS_T} \times 100 \tag{3}$$

Where V_{ER} is the variance of error, SSF is the factorial sum of squares, and DOF_F represents a degree of freedom obtained by subtracting one from the number of levels of each factor (L). The total sum of squares, SS_T, was calculated using the following equation:

$$SS_T = \sum_{j=1}^{m} \left(\sum_{i=1}^{L} Y_i^2\right)_j - mn\left(\overline{Y_t}\right)^2 \tag{4}$$

Y_t is obtained as:

$$\overline{Y_t} = \sum_{j=1}^{m} \left(\sum_{i=1}^{L} Y_i\right)_j / mn \tag{5}$$

Where, *m* represents the number of experimental plots covered in this study, and *n* represents the number of repetitions under the same experimental plot. The factorial sum of squares, SS_F, is given by:

$$SS_F = \frac{mn}{L} \sum_{k=1}^{L} \left(\overline{Y}_K^F - \overline{Y_t}\right) \tag{6}$$

$\overline{Y}_K^F$ is the average value of the measurement results of a certain factor in the *kth* level. Furthermore, the variance of error, V_{ER} was given by:

$$V_{ER} = \frac{SS_T - \left(\sum_{F=A}^{D} SS_F\right)}{m(n-1)} \tag{7}$$

3. Results and discussion

3.1. Sediment yield

The variation of sediment yield depending on the five factors and their levels is shown in Fig 3.4A and 5A respectively. The average amount of sediment yield across replicates varies from 499.2 $\pm$ 20.6 to 60.5 $\pm$ 17.3 g m^{-2}. Plot-based rainfall simulation data show pronounced relative differences in sediment yield among different combinations of factors and their respective levels (Fig. 3.4A). Experimental plot B10 (0 % vegetation cover, a rainfall intensity of 3.4-4 mm min^{-1}, the slope of 4 %, SiltOM 16-18% of and DLL of < 40cm) shows the highest sediment mass with 499.2 g m^{-2}, indicating the highest erosion levels under these conditions. The lowest sediment mass (60.5 g m^{-2}) was obtained at plot L12 (vegetation cover was >15 %, rainfall intensity < 2.5 mm min^{-1}, and slope between 1 and 3 %). Fig 3.5 shows the means of sediment yield for each factor and each level and compares them to the overall factor mean (grand mean, dashed line) (ANOM). These graphs show that the amount of sediment increases with an increase in rainfall intensity (Fig. 3.5A). The minimum rainfall intensity needed to initiate soil erosion, in this study, was 2.5 mm min^{-1}. At lower rainfall intensities, the infiltration rate is higher in the beginning. The potential kinetic energy of raindrops is small and the splash effect is weak and so is the sediment yield. In addition, runoff volume is relatively small under lower rainfall intensities (Mohamadi and Kavian, 2015). The relationship between rainfall intensity and sediment yield varied across intensity levels in a systematic way (Fig. 3.5A). The sediment yield increased to 204.9 g m^{-2} when the RI increased to level 2, which was 73.5 g m^{-2} higher than at RI level 1. The increment was 253.3 g m^{-2} and 310.7 g m^{-2} with RI levels 3 and 4 respectively, where sediment yields were respectively 1.9 and 2.4 times higher than at RI level 1 (Fig. 3.5A). This result may indicate that at the plot scale, soil loss would linearly increase up to a threshold of rainfall intensity, beyond which soil loss would increase non-linearly. Similarly, (Kandel et al., 2004b) found a non-linear relationship between high-intensity rainfall and soil erosion processes. Therefore, it can be suggested that high rainfall intensities resulted in greater soil losses. This is also confirmed by other studies where high intensity rainfall events increased sediment yield (Jebari et al., 2008; Sukartaatmadja et al., 2003; Ziadat and Taimeh, 2013a) and sediment transport.

Soil detachment and runoff significantly increased with rainfall intensity for both uncultivated and cultivated lands (Ziadat and Taimeh, 2013b) but the level of vegetation cover has a significant effect on the soil detachment. As for plot B10, the same rainfall intensity of 3.4−4 mm min^{-1} was applied to plots E3, C5, and L16 producing 188.1 g m^{-2}, 207 g m^{-2}, and 199 g m^{-2} average sediment yield respectively (Fig. 3.4). However, in plot B10 the sediment yield was 499.2 g m^{-2}. Among the rates of sediment yield for four vegetation covers analyzed in this study, vegetation cover level 4 was found most beneficial for preventing soil losses. The eroded sediment yield was below 149 g m^{-2} when the vegetation cover was more than 15 % (level 4). The sediment yield generally tended to decrease with an increase in vegetation cover (Table 3.3). The highest mean sediment yield (averaged across all other factors) was observed after seedbed preparation (vegetation cover 0 %) with 292.16 g m^{-2} (Fig. 3.5A). In this study, increasing vegetation cover dramatically reduces sediment yield which is in accordance with the results of (Donjadee and Chinnarasri, 2012; Lin et al., 2018). (Zapata et al., 2021) mentioned that the vegetation cover interception reduces the diameter of the drops reaching the soil surface and hence reduces the kinetic energy of a raindrop.

(Huang et al., 2012) also described that vegetation cover increases soil surface roughness that acts as a barrier to impede surface runoff and increases infiltration time. Thus, vegetation cover reduces the sediment yield by reducing the kinetic energy of raindrops, intercepting rainfall, increasing surface roughness, and enhancing infiltration times.

A positive relationship was further detected between slope and sediment yield. The sediment yield increased from 162.24 g m^{-2} at a slope of 1 % to 297.44 g m^{-2} at a slope of 5 % Fig. 3.5A. Previous studies also show that the sediment yield increases with increasing slopes. This indicates a strong positive relationship between slope and sediment yield (Grismer, 2012). Under extreme rainfall intensities, it has been observed that surface runoff velocity and sediment yield are primarily driven by slope inclination (Yan et al., 2018). These observations are likely related to higher overland flow velocities at higher slope gradients (Defersha and Melesse, 2012) resulting in higher sediment yield. A gentle slope is less subject to activation and transportation of eroded sediments. Additionally, the splashing effect of raindrops generates surface sealing on gentle slopes producing more surface runoff carrying sediments. Soil particles are detached from the steep slopes where downward gravity is comparatively large. Therefore, there is a tradeoff between rainfall intensity and slope gradient. (Wu et al., 2018b) proved that rainfall intensity has more influence than slope gradient on sediment yield.

The surface soil texture also governs the sediment yield under varying rainfall intensity events. Water availability and water holding capacity are largely dependent on the texture of the soil profile, especially under rain-fed conditions (Libohova et al. 2018; Wang et al. 2020; Zhou et al. 2020). The decreasing concentration of SiltOM in the surface soil showed an increasing trend in sediment yield except for level 4 (2.5 %) which produced a mean sediment yield of 263.52 g m^{-2} which was slightly lower than at level 3 (275.84 g m^{-2}). The detachment of soil is mainly affected by the size and weight of soil particles, organic matter, and the kinetic energy of the raindrops (Sadeghi et al., 2017). The silt content varies from 10.2 to 19.5 % in the study area. The loose particles of silt showed a higher tendency to detachment and erosion process. Soil erodibility increases with increasing silt content (Baruah et al., 2019) but it reduces drastically once the crust is formed. However, SiltOM explicated the strong negative effects of mean weight diameter on splash erosion, and the indirect impact of high organic matter (> 2%) on splash erosion by improving the aggregate stability (Sun et al., 2021). Moreover, With high rainfall intensity and longer test duration, detaching capacity was achieved faster and a surface seal appeared on the soil surface (Michel et al., 2014).

3.2. Surface runoff

At different growth stages of the crop, the runoff process at different rainfall intensities, slope gradients, and soil textures are shown in Fig. 3.4B. The observed mean runoff volume varies between 23.5$\pm$1.07 and 6.54$\pm$0.62 mm among the plots. The plots where rainfall intensity level 4 was applied showed 42.5 % more surface runoff compared to those plots with rainfall intensity level 1. The increase of runoff in the low rainfall intensities was gentle and later it tend to be large. In general, for the highest rainfall intensity, the recorded runoff depth varied from 23 mm to 17.2 mm. On the other hand, for the events with the lowest rainfall intensity, the recorded runoff depth varied from 10. 4 to 6.8 mm. According to the comparison with local meteorological data from the closest weather station, these two classified intensities can be termed as moderate rainfall intensity events and high-intensity storm events respectively. Both of which can produce surface runoff on local slopes in the study area. In our simulation experiments, the rainfall intensity shows a positive relationship with the depth of surface runoff under all vegetation covers. The high rainfall intensity occurring in short duration results in a higher runoff depth (Krisnayanti et al., 2021). The diameter and threshold raindrop velocity tends to increase with higher intensity rainfall. This event is particularly noticeable when the rainfall intensity is at level 4. Heavy raindrops provide more kinetic energy which changes the surface roughness producing pores blockage and soil crusts, which yield higher surface runoff (Lu et al., 2016).

The increasing surface runoff depth is positively related to rainfall intensity at the same slope inclination level and displayed order of 2.5 mm min^{-1} <2.7-3.3 mm min^{-1} < 3.4-4 mm min^{-1} <4 mm min^{-1} (Fig. 3.5B). However, the analyses of the relationship between slope gradient and runoff show increasing surface runoff were observed when the slope increased from 1−3 % (level 2) to >5% (level4) with runoff depth of 10.66 mm and 15.93 mm, respectively. However, it was decreased from 13.573 mm to 10.66 mm despite an increasing slope gradient from <1 % (level 1) to 3 % (level2) and also dropped to 15.08 mm when the slope was >5 % (level 4). The main reason is that observations at slope levels 1 and 2 are performed for soil class 1 and class 2, with high and moderate permeability, respectively (Fig. 3.2A). Previous studies also indicate that surface flow decreases with increasing slope gradient as the rain-bearing area becomes small as at smaller slope gradient the infiltration time is longer at the beginning with high permeable soil conditions (Deng et al., 2019; Wu et al., 2018a). Also, other studies show that surface runoff increases and tend to stabilize with the further increase of the slope gradient (Zhong and Zhang, 2011) but some studies also show that runoff increases first and then start decreasing with increasing slope gradient (Jourgholami et al., 2021; Li et al., 2020; Li and Yu, 2012). The present study shows similar results. Guo et al., (2018) showed that runoff depth is directly related to rainfall intensity and in a negative relationship with slope gradient. Infiltration rates decrease as slope increases from 6° to 35° and, thus, runoff depth increases to a certain extent until a critical slope gradient of 11° is reached at which infiltration rate trend starts changing (Liu et al., 2015). With further increments in slope, the runoff depth gradually decreases (Jourgholami et al., 2021; Nassif and Wilson, 1975). The rainfall intensity has more impact on runoff than slope gradient in this study which is in line with the work by (Wu et al., 2018b). Since the slope gradients at our research site are well below 10 degrees the stronger impact of rainfall intensities agrees with other studies (Liu et al., 2015)

In this study, vegetation cover had a positive relationship with runoff depth. Fig. 3.5B shows that from level 1 (1-5 %) to level 2 (0 %) of vegetation cover there is an abrupt increase in surface runoff as on bare soil there are no interception losses. Then the runoff depth increases with increasing vegetation cover from level 3 (10-15 %) to level 4 (>15 %). The runoff depth was in the order of level 4 > level 2 > level 3 > level 1 of vegetation cover for both high and low rainfall intensity and all slope gradients. However, many studies show that runoff decreases with increasing vegetation cover due to higher canopy interception and rain redistribution reduces energy and runoff depth (He et al., 2020; Loch, 2000; Meng et al., 2007; Tong Li et al., 2020). The reason for high runoff depth at high vegetation cover can be hydrophobic repellency (De Jonge et al., 2007; Hermansen et al., 2019; Knadel et al., 2016) of the surface soil, as higher vegetation cover extracts more soil water. In fact, low soil moisture conditions under higher vegetation cover as noted during the field experiments. Many studies have reported that surface runoff depth increases under dry conditions such as drought periods (Burch et al., 1989; Buttle and Turcotte, 1999; Gomi et al., 2008; Sosa-Pérez and MacDonald, 2017). These studies suggested that the generation of hydrophobic soil surface conditions was one of the main reasons for this phenomenon under dry conditions. (Burch et al., 1989) for example, found that runoff depth increases from 5 % to 15 % due to the hydrophobic conditions after drought or dry summer. These previous studies suggest that because of drought development water repellent soil surface conditions produce more surface runoff regardless of high vegetation cover. The size of the plot can also have a significant impact on the runoff depth. Results obtained by Smets et al. (2008) indicate that there is significant variation in the effectiveness of vegetation cover on runoff if the plot is less than 11m long. Plot scale significantly affects the influence of surface roughness and vegetation cover on sediment yield and runoff depth (Jourgholami and Labelle, 2020).

The runoff depth changed with changing silt and organic matter content among plots and results suggest that effects are significant ($p < 0.027$). The results agree with Vaezi et al. (2010), who also observed that runoff significantly correlated with silt ($p < 0.001$) and organic matter ($p < 0.05$). Organic matter positively affects the soil permeability, hence reducing the surface runoff depth (Sepaskhah and Bazrafshan-Jahromi, 2006). A similar pattern was observed for levels 1, 2, and 4 of this factor with the runoff averaging 14.05 mm, 13.82 mm, and 12.50 mm, respectively. Slightly increasing runoff depth at level 3 was observed. Results agree with studies indicating that the primary factors affecting surface runoff during rainfall simulation experiments are current soil moisture levels, soil texture, slope, and rainfall intensity (Y. Wang et al., 2016; Ziadat and Taimeh, 2013b). The highest runoff was recorded with 23 mm at plot B10 where SiltOM was at level 3 (Fig. 3.4) (Table. 3.4) and depth to loamy layer < 40 cm (Fig. 3.2). Later the runoff depth tends to decrease to 12.4 mm as SiltOM percentage increases in the field to level 4. A general trend in this study depicts that with increasing SiltOM content there is a decrease in surface runoff depth with a slight difference at level 3. The depth to a loamy layer (DLL) may act contrary to the effect of the silt content on runoff depth. A thicker sandy topsoil (i.e. deeper depth to loamy layer) may positively affect the soil permeability increasing the infiltration and consequently reducing the surface runoff depth. Thus, spatial variation in these soil properties in the study area noticeably influences the runoff generation in the test plots. This has been also proved in previous studies (Brakensiek and Rawls, 1994; Hrabovskỳ et al., 2020; Meena et al., 2020) mentioning that spatial variability of infiltration capacity is related to the spatial variability of topsoil characteristics that consequently affect the runoff generation.

3.3. Carbon and Nitrogen concentration in sediment yield

Soil carbon and nitrogen concentration redistribution is strongly governed by the amount of detached sediment within cultivated lands and it is generally accepted that C and N are preferentially transported during soil erosion (Holz and Augustin, 2021). The average values of carbon and nitrogen losses under each level of vegetation cover, slope, and rainfall intensities are presented in Fig. 3.4C & D respectively. Nitrogen and carbon contents of observed sediment yields are highly correlated and vary among experimental plots (Fig 3.4. C & D). Total C and N losses ranged between 12$\pm$1.02 to 3.29$\pm$0.496 g m^{-2} and 0.948$\pm$0.073 to 0.106$\pm$0.016 g m^{-2} respectively with moderate to high standard deviation, depending on RI, vegetation cover percentage, and SiltOM content (Fig. 3.4. C & D). As reported for the soil loss, C and N losses on the plots were positively related to the rainfall intensity ranging between 2.8 to 7.7 g m^{-2} and 0.2 to 0.4 g m^{-2} (Fig. 3.4).

In Fig. 3.5C and 3.5D, it is obvious that the highest nutrient losses were found at vegetation cover more than 0 % despite other land covers percentages contributing less to the nutrient losses (Fig. 3.5 C & D). However, C and N losses were higher in at a vegetation cover of 15 % and in barren land when the soil was subjected to rainfall intensity level 4 (4 mm min^{-1}) (Fig. 3.4. C & D). This behavior is related to the absence of topsoil protective cover that reduces the impact of raindrops and detachment of soil particles (Nunes et al., 2011). The highest C loss was found under RI of > 4 mm min^{-1} with values ranging between 12$\pm$1.02 g m^{-2} and 7.68 $\pm$1.12 g m^{-2} after 8 min rainfall, respectively for vegetation cover levels 4 and 3 (Fig. 3.5C). Regarding N losses, the highest losses were recorded in the plots with the highest C losses. The smallest C and N loss was observed as 2.8 and 0.2 g m^{-2} respectively at low rainfall intensities when detachment forces were small (Fig. 3.5 C & D). The experiments carried out in this study confirm the soil susceptibility to loose nutrients under specific vegetation cover, even at a low rainfall intensity level (< 2.5 mm min^{-1}). All the study plots have varying silt and organic matter contents, which made soils to lose nutrients defining crusting indexes (Awadhwal and Thierstein, 1985). The different values of runoff induce differences in sediment yield and transport of nutrients. Higher rainfall intensities produce higher runoff depth. It could be confirmed that nutrient losses increase exponentially with higher rainfall intensities. The analysis of slope gradient effect on nutrient loss, where higher soil losses occur, shows that soil sealing can be the main factor that limits runoff as it does not increase significantly with increasing slope (Fig. 3.5B) (Ramos et al., 2019). However, as sediment yields are increasing with an increasing slope so do the C and N losses captured in the collected sediments except at slope level 3 where C and N losses are reduced as slope increases from level 2 to level 3. The reason is probably that the plots with slope level 3 lie in soil class 3 with throughout sandy texture and lower C and N concentrations in the topsoil (Yost and Hartemink, 2019). The results suggest that a permanent vegetation cover is essential to reduce C and N losses.

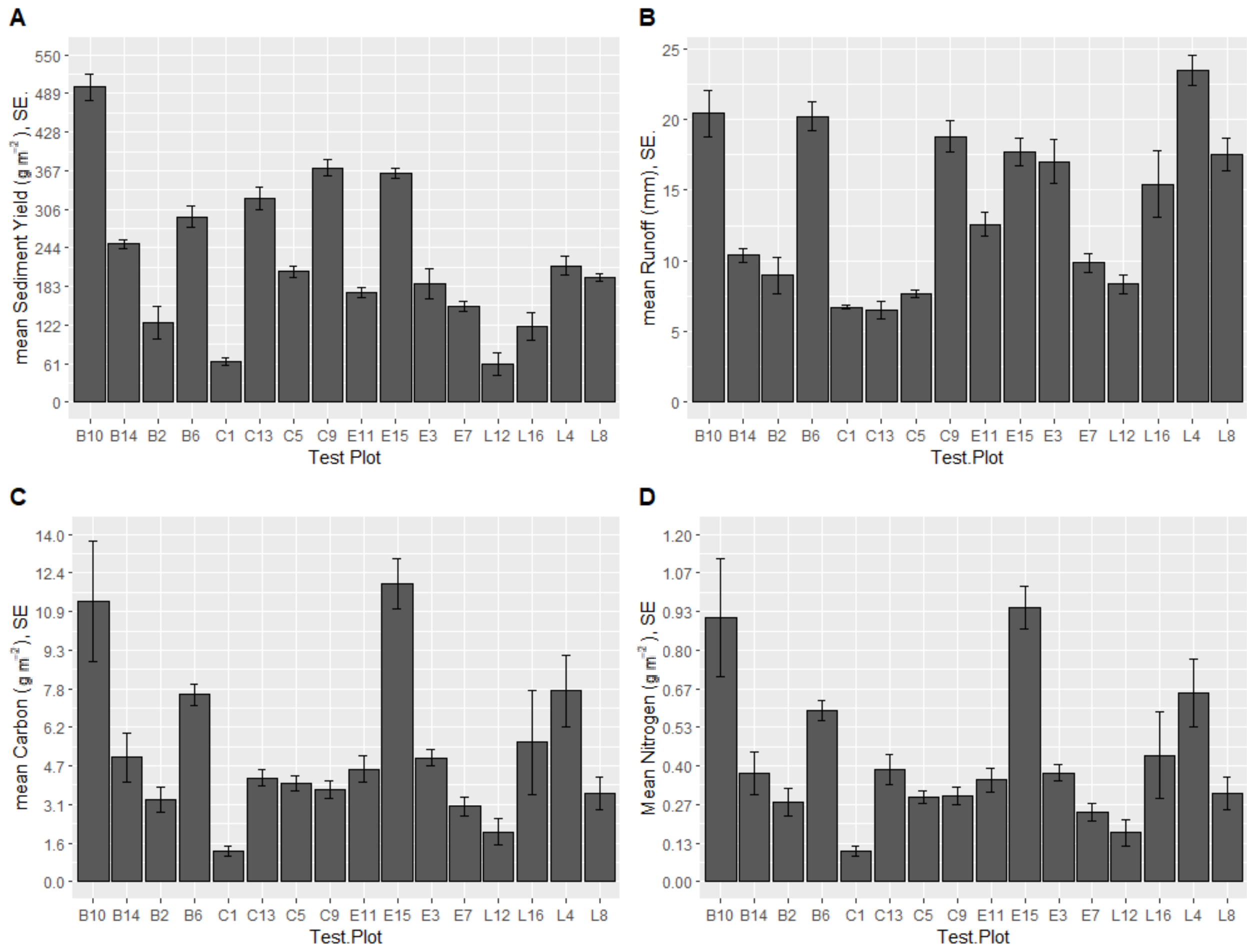


Fig. 3. 4: Mean temporal variations and standard error (SE) in sediment yield, runoff, carbon, and nitrogen in relation to heterogeneous field conditions

Table 3. 3. Mean sediment yield observed under changing soil surface conditions (vegetation cover factor levels)

Field condition	Vegetation cover	Mean sediment yield	Standard error
	%	g m^{-2}	g m^{-2}
Cultivation	5	241	31.1
Seedbed reparation	0	292	35.8
Emergence stage	10	219	22.5
Leaf development (3 Leaves unfold)	15	149	17.7

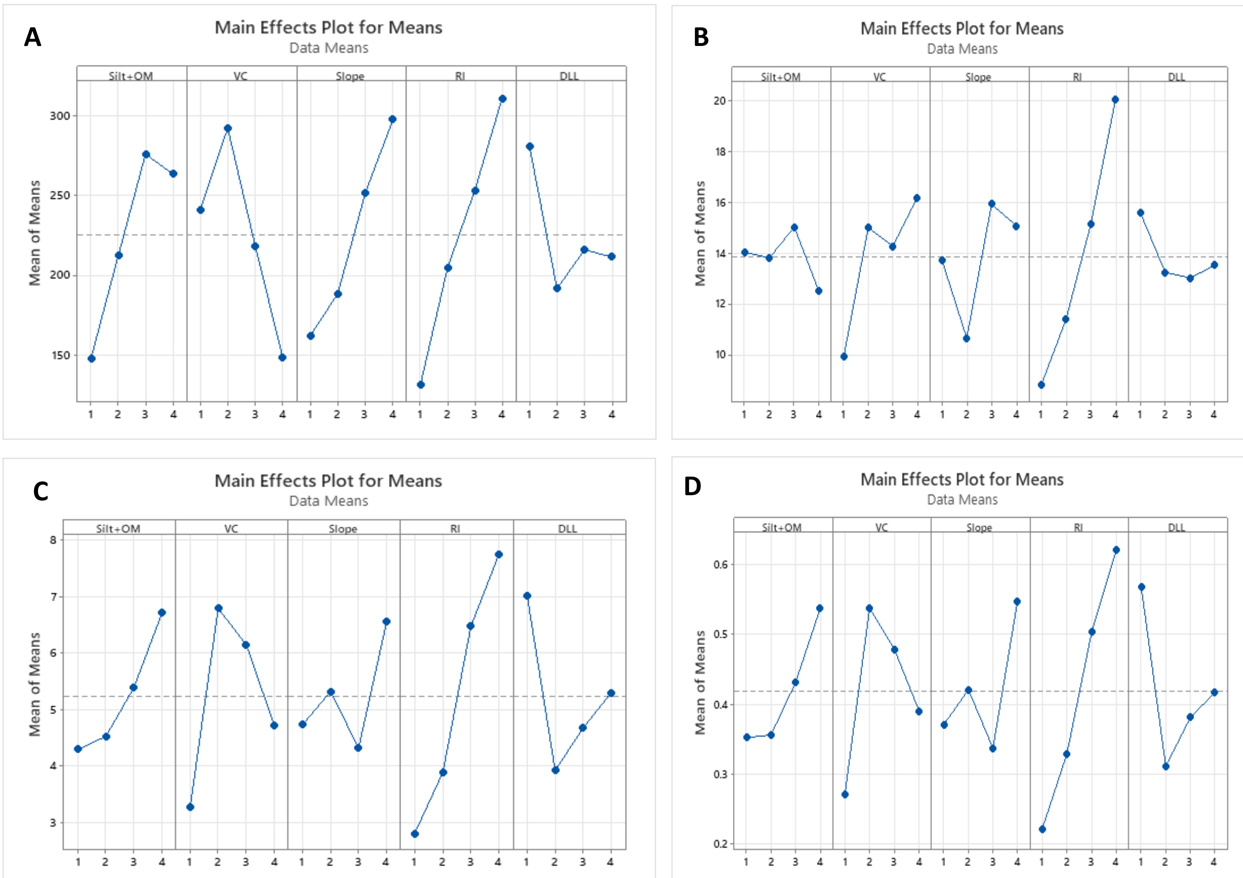


Fig. 3. 5: Analysis of means (ANOM)) for A: Sediment yield (g m^{-2}), B: Runoff (mm), C: Carbon (g m^{-2}), D: Nitrogen content (g m^{-2}). Mean values for each level of each factor (blue dots) and the overall mean of each factor (dashed green line) are shown.

3.4. Optimal conditions for maximum sediment yield, surface runoff, Nitrogen, and Carbon content

The obtained S/N ratio responses for sediment yield, surface runoff, carbon, and nitrogen content are shown in Table 3.4 and Table 3.5. A Higher S/N ratio implies low variations between the desired output and the measured output. The maximum S/N ratio values among the 16 experiments, indicated in table 3.4 were 53.97 for sediment yield and 26.21 for runoff, 21.59 and -0.81 for C and N losses respectively in the test plot 10 with factor combination of $SiltOM_3$-VC_2-SS_4-RI_3-DLL_1 (Table 3.4). Inserting these values from table 3.4 into Eqn. 2 resulted in mean values of S/N ratios for each factor level. The maximum values of means of the S/N ratio were then identified. The bold values in Table 3.5 show the factor level with the highest S/N ratio for each factor and output variable (sediment yield, runoff, C and N losses). The highest mean S/N ratio for sediment yield was obtained at factor level 4 for SiltOM, SS, and RI, at level 2 for VC, and level 1 for DLL (Table 3.5). Thus, we can predict that the highest sediment yield should be obtained with the factor level combination $SiltOM_4$-VC_2-SS_4-RI_4-DLL_1 (Table 3.5). On the other hand, the lowest sediment yield should be obtained with the factor combination $SiltOM_1$-VC_4-SS_1-RI_1-DLL_2. The estimated optimum factor level combination for obtaining the highest surface runoff was found to be $SiltOM_3$-VC_4-SS_3-RI_4-DLL_1 (Table 3.5). The highest rainfall intensity (>4 mm min^{-1}) led to the highest volumes of runoff, followed by the factor vegetation cover (maximum values at Level 4) (Table 3.5). Earlier studies showed that surface runoff depth is sensitive to the plot size and type of vegetation (Herweg and Ludi, 1999; Kort et al., 1998; Zuazo and Pleguezuelo, 2008). The optimum condition for maximum C and N losses were found to be $SiltOM_4$-VC_2-SS_4-RI_4-DLL_1 and $SiltOM_4$-VC_2-SS_4-RI_4-DLL_1 respectively (Table 3.5). The results indicate that rainfall intensity was the main factor that most influenced the sediment yield, runoff, C and N losses in the study area followed by vegetation cover and then slope steepness.

Table 3. 4. The S/N ratio of each experiment resulting from a different combination of factors and levels.

Factors/ Plot	Combination of levels					Silt OM (%)	vegetation cover (%)	Slope steep-ness (%)	Rainfall intensity (mm min^{-1})	Depth to loamy layer (cm)	S/N			
	Silt OM	VC	SS	RI	DLL						Sediment yield	Runoff	C	N
1	1	1	1	1	1	>20	1-5	<1	<2.5	<40	36.08	16.53	1.65	-19.47
2	1	2	2	2	2	>20	0	1-3	2.7-3.3	40-55	41.98	19.05	10.35	-11.20
3	1	3	3	3	3	>20	10-15	3-5	3.4-4	55-70	45.47	24.62	13.96	-8.48
4	1	4	4	4	4	>20	>15	>5	>4	>70	46.70	27.42	17.71	-3.72
5	2	1	2	3	4	18-20	1-5	1-3	3.4-4	>70	46.31	17.70	11.96	-10.69
6	2	2	1	4	3	18-20	0	<1	>4	55-70	49.35	26.12	17.55	-4.56
7	2	3	4	1	2	18-20	10-15	>5	<2.5	40-55	43.60	19.87	9.65	-12.44
8	2	4	3	2	1	18-20	>15	3-5	2.7-3.3	<40	45.95	24.87	11.01	-10.35
9	3	1	3	4	2	16-18	1-5	3-5	>4	40-55	51.39	25.48	11.43	-10.58
10	3	2	4	3	1	16-18	0	>5	3.4-4	<40	53.97	26.21	21.59	-0.81
11	3	3	1	2	4	16-18	10-15	<1	2.7-3.3	>70	44.75	21.98	13.13	-9.09
12	3	4	2	1	3	16-18	>15	1-3	<2.5	55-70	35.63	18.42	6.02	-15.45
13	4	1	4	2	3	<16	1-5	>5	2.7-3.3	55-70	50.18	16.31	12.41	-8.20
14	4	2	3	1	4	<16	0	3-5	<2.5	>70	47.97	20.32	13.99	-8.54
15	4	3	2	4	1	<16	10-15	1-3	>4	<40	51.18	24.95	21.05	-0.46
16	4	4	1	3	2	<16	>15	<1	3.4-4	40-55	41.52	23.76	15.01	-7.19

Table 3. 5. Mean S/N ratio response table for the investigated experimental factors

Output Parameter	Experimental factors	Mean S/N ratio				Delta	Rank
		Level 1	Level 2	Level 3	Level 4		
Sediment Yield	Silt+Organic matter	42.56	46.30	46.44	**47.71**	5.15	4
	Vegetation Cover	45.99	**48.32**	46.25	42.45	5.87	2
	Slope Steepness	42.92	43.78	47.69	**48.61**	5.69	3
	Rainfall Intensity	40.82	45.71	46.82	**49.65**	8.83	1
	Depth to Loamy Layer	**46.79**	44.62	45.16	46.43	2.17	5
Runoff	Silt+ Organic matter	21.91	22.14	**23.02**	21.34	1.69	5
	Vegetation Cover	19.01	22.93	22.86	**23.62**	4.61	2
	Slope Steepness	22.1	20.03	**23.82**	22.45	3.79	3
	Rainfall Intensity	18.79	20.56	23.07	**25.99**	7.21	1
	Depth to Loamy Layer	**23.14**	22.04	21.37	21.86	1.78	4
Carbon	Silt+ Organic matter	10.92	12.54	12.91	**15.75**	4.83	3
	Vegetation Cover	9.36	**15.74**	14.58	12.44	6.37	2
	Slope Steepness	11.83	12.48	12.60	**15.21**	3.37	4
	Rainfall Intensity	7.83	11.73	15.50	**17.07**	9.24	1
	Depth to Loamy Layer	13.83	11.61	12.49	**14.20**	2.59	5
Nitrogen	Silt+ Organic m	-10.72	-9.51	-8.98	**-6.10**	4.61	3
	Vegetation Cover	-12.24	**-6.28**	-7.62	-9.18	5.95	2
	Slope Steepness	-10.08	-9.45	-9.49	**-6.29**	3.78	4
	Rainfall Intensity	-13.97	-9.71	-6.79	**-4.83**	9.14	1
	Depth to Loamy Layer	**-7.77**	-10.35	-9.17	-8.01	2.58	5

3.5. Percentage contribution of the experimental factors to sediment yield, runoff, C and N losses

ANOVA was used to estimate the contribution of the individual factors to sediment yield, runoff, C and N losses (Table 3.6). Rainfall intensity contributed most strongly to sediment yield (40.55 %) followed by slope steepness (23.76 %) and vegetation cover (17.73 %). (Peng and Wang, 2012) indicated that soil loss is positively related to rainfall events with high antecedent precipitations. The slope gradient can be more important than vegetation cover because of its relation with the underlying geological formations resulting in varying soil characteristics. In consequence, slope gradients are related to soil moisture and hence the soil's susceptibility to soil detachment. Vegetation cover yields higher soil moisture at low to moderate slopes but it falls sharply at steeper slopes as soil permeability decreases that increases runoff till a threshold slope, moreover, the flow velocity becomes larger with increasing slope gradient due to increasing shear stress (Defersha and Melesse, 2012). The impact duration of runoff on steeper slopes becomes smaller and hence it weakens the protecting effect of surface seal, increasing the impact of rainfall splashing on the soil surface (Zhao et al., 2015). It produces more detachment of soil particles and transportation. However, the sum of silt content and organic matter only contributes 14.77 % to sediment yield. (Ziadat and Taimeh, 2013a) showed a significant correlation between the ultimate infiltration rate and soil properties such as organic matter (R = 0.48) and silt content (R = 0.72). The low contribution of silt and organic matter to our results is most likely related to their comparatively low variation among measurement plots and due to the high content of organic matter that is varying from 2.3 to 2.4 % among the test plots. The high organic matter improves the aggregate stability, reduces the bulk density, and increases moisture retention and soil shear strength that helps in soil stability and resistance against erosion (Ekwue, 1990). Previous studies also concluded that aggregate stability is closely and negatively related to the soil detachment from field experiments under rainfall simulators on micro plots (Roth et al., 1987; Van Dijk et al., 1996). The factor of least importance in our study was the depth to the loamy layer (DLL) (3.17 %). This can be explained by the fact that the loamy layer with low permeability generally starts at relatively deep depths (lowest depth approximately 38 cm) and at many locations sand-filled pre-glacial ice cracks with higher permeability were observed in the loamy layer (Kühn, 2003). Therefore, differences in permeability and water storage capacity (risk of waterlogged soils) between experimental plots were probably relatively low. ANOVA results for the nitrogen (N) and carbon (C) content of sediment yield were similar (Table 3.6). As for sediment yield, rainfall intensity contributed most to the overall variation of C and N contents. The respective percentage contribution of rainfall intensity, vegetation cover, SiltOM content, slope and depth to loamy layer was 51.70%, 21.50 %, 12.55 %, 9.63 % and 4.62 % respectively for Nitrogen content and 52.31 %, 24.07 %, 12.39 %, 6.81 % and 4.41 % respectively for Carbon content. Runoff was mostly influenced by rainfall intensity (55.45 %) followed by vegetation cover, slope, depth to loamy layer, and SiltOM content. The respective contribution was 55.45 %, 24.71 %, 3.18 %, and 2.78 % (Table 3.6), agreeing with the findings of (Kirkby et al., 2004). The stronger impact of vegetation cover compared with the slope can be explained by the stronger variability of vegetation cover at different soil management stages during the experimental period in the study area. In addition, at different slope levels varying soil compositions and moisture content affect the potential of surface runoff.

Table 3. 6. Percentage contribution of each factor (ρF %) for the different output parameters as estimated by ANOVA

Output Parameters	ρ_F %				
	SiltOM	**Vegetation cover**	**Slope steepness**	**Rainfall intensity**	**Depth to Loamy Layer**
Sediment yield	14.77	17.74	23.77	**40.56**	3.17
Runoff	2.78	24.71	13.88	**55.45**	3.18
Nitrogen content	12.55	21.50	9.63	**51.70**	4.62
Carbon content	12.39	24.07	6.81	**52.31**	4.41

3.6. Linear regression models

Linear regression models are used to predict sediment yield, runoff, as well as C and N losses as a function of Silt + OM, vegetation cover, slope, rainfall intensity, and depth to the loamy layer. No transformation has been performed on the response variables. The estimated regression models are shown in the Eqns. (8-11).

Sediment yield = -7.2 + 40.9 SiltOM - 35.1 VC + 46.9 Slope + 58.6 RI - 18.4 DLL

(R^2 = 82.53) (8)

Runoff = 0.10 - 0.341 SiltOM + 1.807 VC + 0.933 Slope + 3.743 RI - 0.641 DLL

(R^2 = 79.66) (9)

C = -2.08 + 0.810 SiltOM + 0.371 VC + 0.446 Slope + 1.736 RI - 0.440 DLL

(R^2 = 60.97) (10)

N = -0.172 + 0.0629 SiltOM + 0.0299 VC + 0.0445 Slope + 0.1373 RI - 0.0381 DLL

(R^2 = 62.13) (11)

Where sediment yield, runoff depth, C and N are g m^{-2}, SiltOM and VC reprsents levels.

The capability of these empirical regression models was checked by using the coefficient of determination R^2. Regression models for sediment yield, runoff, carbon, and nitrogen yielded R^2

values of 82.53 %, 79.66 %, 60.97 %, and 62.13 % respectively. Residual plots (Fig. 3.6 A, B, C & D) indicate that residuals are independent and normally distributed. Sediment yield is positively related to SiltOM but runoff depth is negatively related. This indicates that a high amount of SiltOM would increase the erodibility of the soil but would reduce the runoff rate. This is also evident from Fig. 3.5A and B. The sediment yield is more sensitive to SiltOM compared to runoff. Coefficients of SiltOM for C and N losses show a positive relationship. C was more responsive to SiltOM as compared to N. It is suggested to have further research to find a threshold point for SiltOM in the soil to achieve the lowest sediment yield and runoff. Fig. 3.7 represents the scatter plot of predicted vs observed values with high R^2. The shaded band is a pointwise 95 % confidence interval on the fitted values. These results confirm the ability of the Taguchi method for the prediction of soil erosion in response to different combinations of factors/levels. The regression equation for sediment yield was further applied to predict sediment yields across the entire field for identifying areas within the field that have a higher susceptibility to soil erosion (Fig. 3.8).

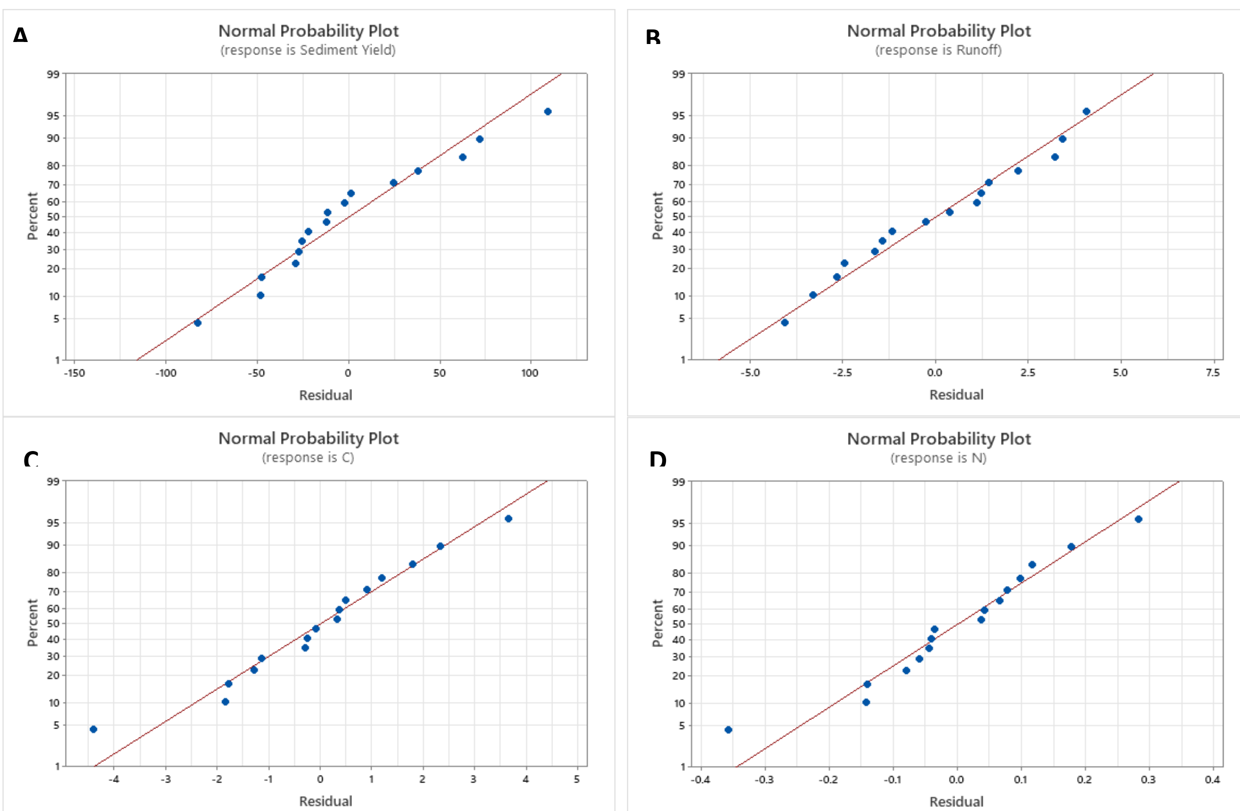


Fig. 3. 6: Distribution of residuals of the regression models for sediment yield, runoff, carbon, and nitrogen

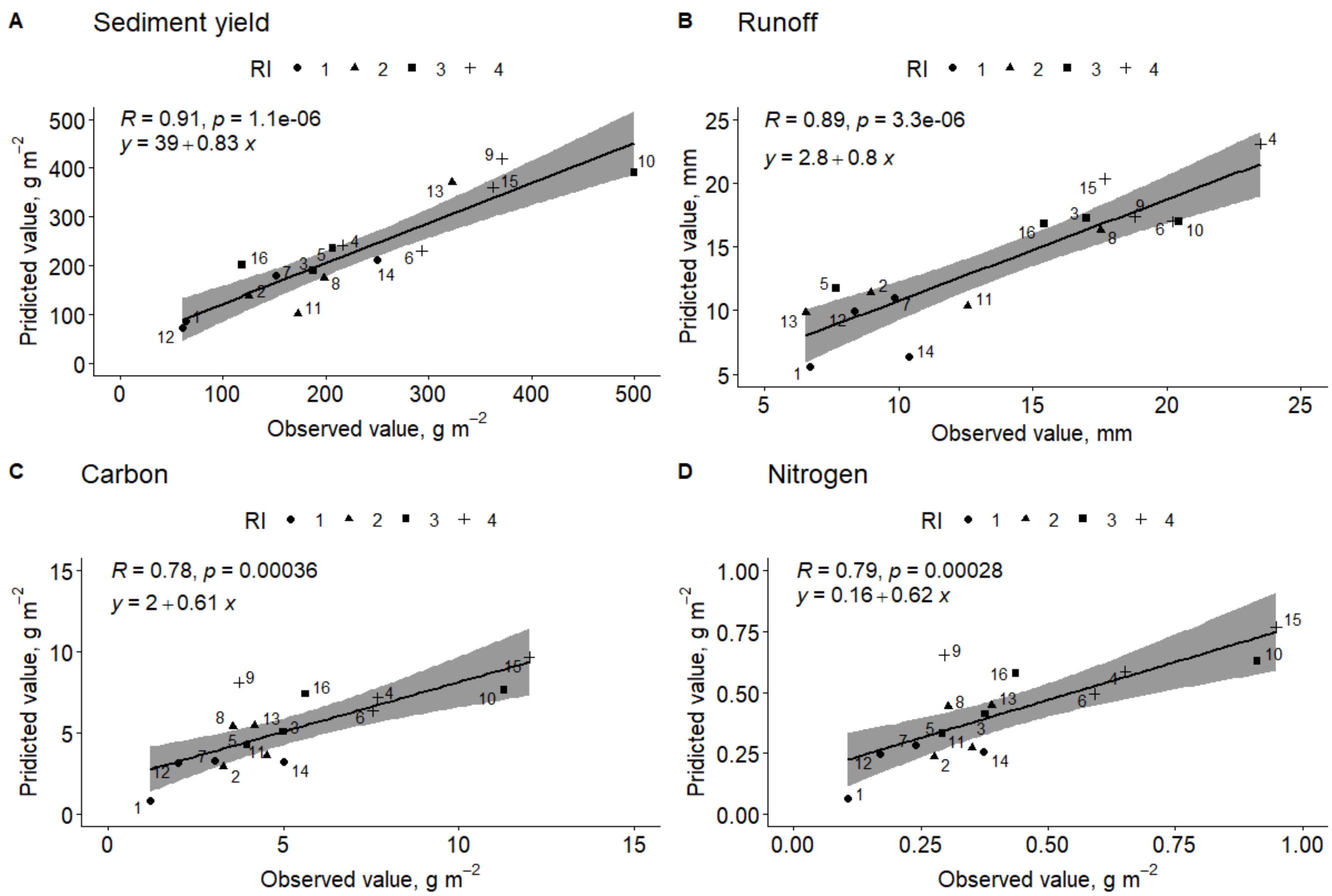


Fig. 3. 7: Predicted versus observed sediment yield, runoff depth, carbon, and nitrogen losses

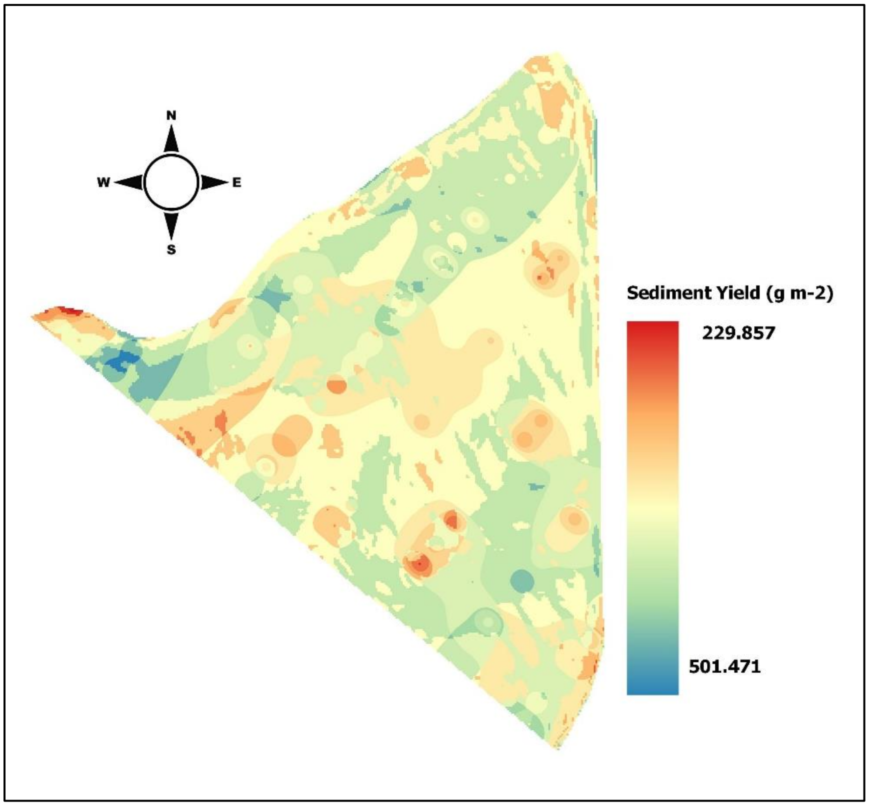


Fig. 3. 8: Identification of potential soil erosion risk areas

4. Conclusion

Different scenarios were tested with 16 effective simulated rainfall events under different rainfall intensities, vegetation cover, heterogeneous in-field slope, and soil conditions. The results indicated that runoff, soil, and CN losses increase with increasing rainfall intensity. it was observed that sediment yield, overland flow, CN content were greatly affected by rainfall intensity having a contribution of 40.56 %, 55.45 %, 51.70 %, and 52.31 % respectively among the other factors. However, the least contributing factor was depth to loamy layer for all output variables except for surface runoff. The results show that the worst conditions among 16 plots were at $SiltOM_3$-VC_2-SS_4-RI_3-DLL_1 for sediment yield. However, predicted experimental factors for the highest sediment yield were found with the factor combination $SiltOM_4$-VC_2-SS_4-RI_4-DLL_1 and the lowest sediment yield was observed with the factor combination $SiltOM_1$-VC_4-SS_1-RI_1-DLL_2. The threshold rainfall intensity for soil erosion was 2.5 mm min^{-1}. VC and DLL are inversely correlated with sediment yield, while SiltOM, slope, and rainfall intensity are directly correlated.

The surface runoff was negatively related to SiltOM and DLL, but the vegetative cover, slope, and rainfall intensity positively affect the runoff. Regarding, C and N, except the DLL, other factors show a positive correlation. Based on the experimental results, statistical regression models were developed, which were applied for identifying the erosion risk areas at the field scale. The applied workflow allowed for efficiently predicting soil erosion and identifying areas susceptible to soil loss at a high spatial resolution. The study approved the capabilities of Taguchi's fractional factorial design to efficiently analyze the response of soil erosion to dominant driving factors and detect and quantify in-field heterogeneity of erosion risk areas. The statistical models generated in this study can be used by environmental agencies and farmers for spatially explicit application of erosion control measures within fields with high spatial heterogeneity. Further, it is suggested that combining GIS with such numerical models can give great benefits for water quality control and soil management on larger scales with intensive spatial heterogeneous field conditions.

Chapter 4

Comparison of predictive modeling approaches to estimate soil erosion under spatially heterogeneous field conditions

This chapter has been submitted in Journal “Environmental Modelling & Software”

1. Introduction

Soil systems are one of the key components affecting ecosystem services (Baer and Birgé, 2018; Baveye et al., 2016; Bouma et al., 2022) upon which many policies depend, including those crucial for water and nutrient cycling, agricultural sustainability, and climate change (Elbasiouny et al., 2022). However, soil systems are subjected to degradation processes such as soil loss through water and wind erosion, which can be caused by inappropriate land management and is expected to intensify with climate change (Chalise et al., 2019). Soil erosion causes loss of fertile topsoil, organic matter, and essential nutrients (Peri et al., 2022), as well as reduction of rootable soil depth leading to crop yield losses (Pimentel, 2006). Soil erosion by water accounts for the biggest share of soil loss in Central European agricultural ecosystems (Panagos et al., 2015). Studies in Lower Saxony, Germany show the highest annual loss on a single field was 53.07 t ha^{-1} y^{-1} (Steinhoff-Knopp and Burkhard, 2018). In addition, a significant increase is predicted in the frequency and magnitude of soil losses due to increasing rainfall intensities caused by changing climatic patterns (Fonseca et al., 2014).

In recent years, a large number of runoff and soil erosion models with different representations of erosion and sedimentation processes have been developed (Raza et al. 2021). Their output differences and the resulting influence on model predictions have been the subject of several reviews (Raza et al., 2022a, 2021). Laboratory studies, small-scale in-field experiments, and empirical and physically-based erosion models have proved to be good tools to investigate these processes (Pandey et al., 2016). Moreover, these tools can help to understand the impact of heterogeneous soil physical and hydrological characteristics, climate variability, and floods on soil erosion, and hence help to improve controlling measures.

Several large-scale soil erosion modeling approaches such as EUROSEM (Kinnell, 1999), MUSLE (Sadeghi et al., 2014), SEDD (Ferro and Porto, 2000), and PSIAC (Garg and Jothiprakash, 2012) have been studied and examined (Raza et al., 2021). Despite their ability to investigate, and predict soil erosion processes, most of these models do not provide reliable erosion prediction over spatially heterogeneous soil cover and soil physical properties at the field scale (Jetten et al., 1999). The main reasons for uncertainties in the erosion predictions are (1) Low spatial and temporal resolution of input data (de Vente and Poesen, 2005) (2) inefficient parameterization (Feng et al., 2010) (3) unfitting calibration (Mondal et al., 2017). For instance, quality erosion predictions with a simple empirical RUSLE model using low detailed input data over a large catchment require intensive calibration. Another limitation comes from the assumption that the soil properties (e.g., particle composition, and soil moisture content) are spatially uniform, whereas the spatial variability of these properties can be very high, even at the scale of a single field. In particular, spatial variability is known to have significant impacts on crop growth and soil water relationship in dynamic erosion modeling. Moreover, a few dynamic models have been developed to simulate erosion processes over a certain period, but they do not necessarily consider dynamic variables such as soil-water balance and vegetation cover (Schymanski et al., 2009).

Temporally dynamic erosion estimations have been conducted with several landscape models such as SWIM (Krysanova et al., 2005), IQQM (Simons et al., 1996), TOPMODEL (Beven et al., 1984), and LASCAM (Zammit et al., 2003). Such models tend to predict accurately sediment transport and deposition but their application is normally limited due to a lack of input information, poor representation of vegetation dynamics as well as uncertainties related to the parameters involved. Most often, these models require detailed input data and outstanding computing systems.

To address some of these issues related to conventional soil erosion modeling, a few erosion models are integrated into agroecosystem models (i.e., simulating soil water and crop growth in high temporal resolution). In this study, an attempt was made to integrate dynamic erosion models and a crop growth model to be applied at the field scale using the Scientific Impact assessment and Modeling (SIMPLACE) platform. SIMPLACE is a flexible modeling platform for advanced agroecosystem analysis that allows the combination of multiple components in a model solution (Gaiser et al., 2013b). The integrated model simulates the dynamics of vegetation cover under specified field management schemes, runoff, and erosion processes.

Only a few studies have been conducted using dynamic models to simulate erosion under heterogeneous soil and crop growth conditions at the field scale. Therefore, this study was undertaken to test the capabilities of the integrated model solution to simulate soil erosion under highly heterogeneous field conditions and to compare its performance with a statistical model for the field conditions. Given the foregoing, the main objective of this research is to provide insights into the uncertainties involved in the simulation of sub-field scale runoff and soil erosion processes due to the model structure and parameter estimation.

2. Material and methods

2.1. Experimental site description

Measurements were conducted at a field site at Großmutz in Löwenberger Land municipality, in the north part of the federal state of Brandenburg, Germany (52° 56' 25.548" N, 13°7'57.648" E) (Fig. 4.1). Brandenburg has a temperate humid climate zone. The research area has 6.25 ha and is characterized by heterogonous soil conditions with undulated slopes ranging between 1% and 7 %. Topsoil texture is classified as silty and medium to loamy sand. Soil physical and hydrological properties vary across the slopes in the research site. The field is undulating which has led to differences in edaphic and hydrological features, with terrain height averages from 51.5 to 57.5 m a.s.l. and pronounced slope gradients (Fig. 4.1). The climate of the region is temperate and humid with average rainfall of 554 mm year^{-1} (Gutzler et al., 2015) and mean annual temperatures between 7.8 °C and 9.5 °C (Ihinegbu and Ogunwumi, 2021, German weather station 2020). The daily mean weather data from (January 2019–September 2022) are presented in Fig. 4.2.

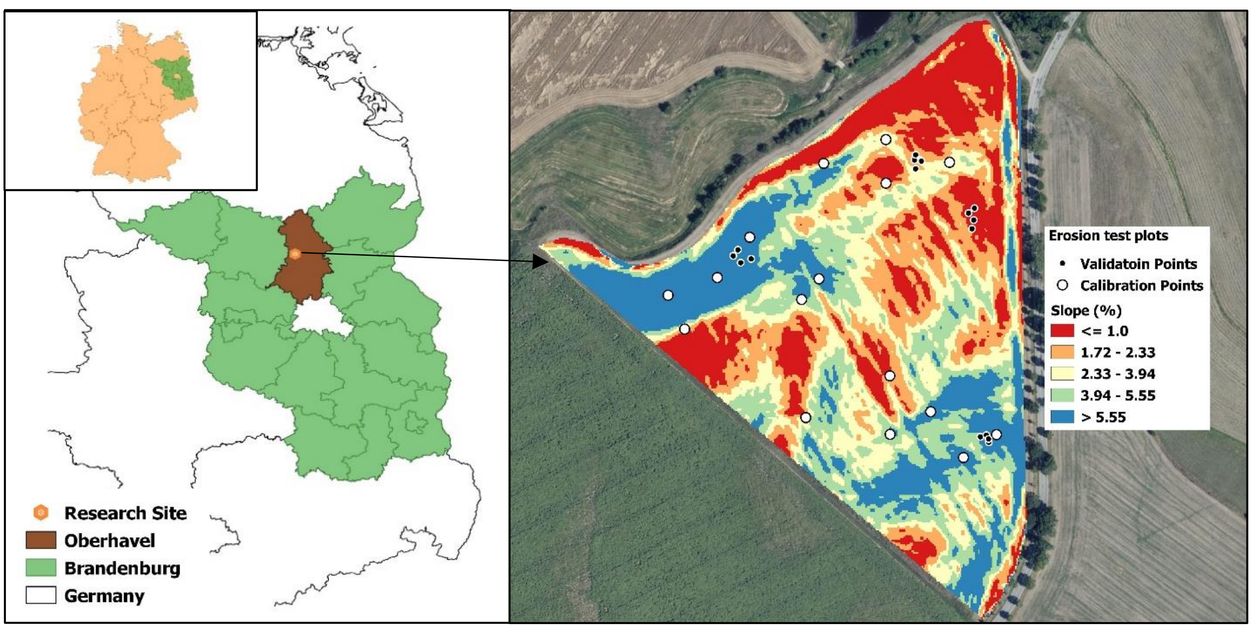


Fig. 4. 1: Experimental site in Löwenberger Land, Brandenburg, Germany, (May 8th, 2020, Google Earth). The site topography was derived from the 2008 LiDAR imagery (https://geobroker.geobasis-bb.de).

Crop growth and development stages were regularly monitored with biomass sampling and leaf area index (LAI) measurements. Destructive samples were taken for monitoring cop phenological stages and fresh and dry biomass. Non-distractive samples were taken for crop height and LAI measurements. Data on the soil physical and hydrological properties was derived from field surveys at 87 different soil augering locations and subsequent laboratory analyses (Table 4.1). Erosion measurements were taken from 16 plots with factorial combinations of the depth to a loamy layer, slope inclination, and soil organic matter (SOM). On-field erosion, runoff, and crop-related observations and measurements were conducted at different times (Table 4.2). The 16 locations were considered to be well distributed in the research site (Fig. 4.1, Table 4.1) (Raza et al., 2022b). Details of the scheme for the selection of these points have been mentioned in (Raza et al., 2022).

Table 4. 1. Tests plots with factorial combinations for measuring soil erosion using a rainfall simulator

Plot	Slope %	SOM %	K	LAI m^2/m^2	λ	Rainfall intensity mm/min	Applied rainfall Mm	Total soil water holding capacity mm
1	1.48	2.30	0.30	0.01	0.165	<2.5	16.24	103.42
2	2.9	2.48	0.33	0	0.200	2.7-3.3	18.72	84.78
3	3.1	2.27	0.34	0.15	0.115	3.4-4	29.88	95.05
4	4.8	1.88	0.37	0.2	0.083	>4	35.52	73.09
5	3.8	2.47	0.29	0.1	0.165	3.4-4	22.9	92.54
6	1.79	2.40	0.32	0	0.200	>4	32.4	92.45
7	4.78	1.85	0.33	0.15	0.115	<2.5	19.96	90.76
8	3.3	2.15	0.35	0.2	0.083	2.7-3.3	30.72	92.45
9	4.07	2.03	0.31	0	0.165	>4	30.72	87.21
10	5	2.20	0.29	0	0.200	3.4-4	32.56	76.62
11	2.47	2.63	0.25	0.15	0.115	2.7-3.3	23.44	69.63
12	2.23	2.12	0.27	0.2	0.083	<2.5	19.44	76.80
13	8.02	2.50	0.34	0.1	0.165	2.7-3.3	16.8	73.52
14	4.65	2.47	0.28	0	0.200	<2.5	19.8	90.45
15	4.36	2.43	0.25	0.15	0.115	>4	30.2	88.78
16	2.57	2.42	0.31	0.2	0.083	3.4-4	28.24	87.85

SOM: soil organic matter, K: soil erodibility factor, LAI: leaf area index measured with SunScan Canopy Analysis System, λ: efficiency of entrainment,

Table 4. 2. List of data collection activities for calibration and validation

Purpose	Activity	Date	Crop
calibration	Runoff/Erosion	2020-2021	-
	LAI/Biomass	2019-2020	Winter Triticale
	LAI/Biomass	2021-2022	Rapeseed[1]
validation	Runoff/Erosion	2021	-
	LAI/Biomass	2020-2021	Winter Triticale
	LAI/Biomass	2021-2022	Rapeseed[2]

Rapeseed[1]: Half samples (13 points) were used for calibration, Rapeseed[2]: Half samples (13 points) were used for validation

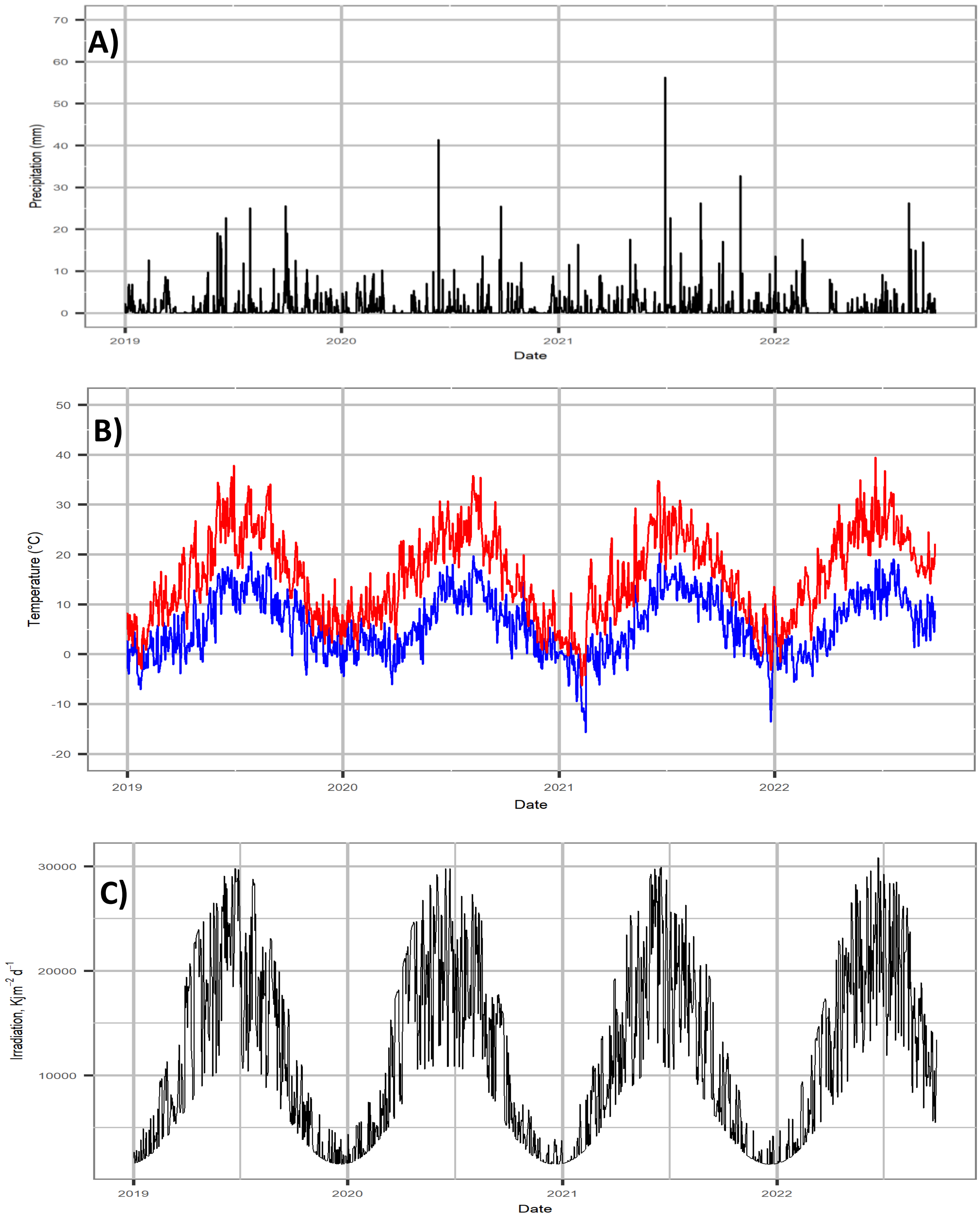


Fig. 4. 2: **Weather in research site; (A) cumulative daily precipitation; (B) mean daily maximum (red) and minimum (blue) temperature; (C) mean daily irradiation over the experimental period. This weather data was collected from the weather station network maintained by the Deutscher Wetterdienst (DWD).**

2.2. General overview of the modeling structure

Within the modeling framework SIMPLACE (simplace.net), a model solution was designed which combines dynamic crop growth (Lintul5) (Ewert et al., 2011), and soil water balance (SlimWater, (Addiscott and Whitmore, 1991) with the runoff curve number approach (Shi et al., 2009) and two soil erosion methods, namely Freebairn and Rose. A third approach was the application of a locally-based statistical model developed for the site conditions by (Raza et al., 2022c). The three approaches to model soil erosion were chosen for the following reasons:

1. The approaches of Freebairn (Freebairn and Wockner, 1986) and Rose (Silburn, 2011) have been widely used, e.g, Freebairn model in (Bahri et al., 2019; Connolly et al., 2002; Dang et al., 2015; Yang et al., 2018), and Rose model in (Rose, 2001)
2. Freebairn and Rose models provide provision to understand soil water dynamics by integrating runoff parameter
3. A local statistical model was developed based on the observations from rainfall simulator experiments at the study site (Raza et al., 2022c)

The selected Freebairn and Rose soil erosion models are empirical approaches to simulate sediment yield and were combined with sub-models for estimating runoff and aboveground soil cover in a mechanistic way. The main drivers determining the sediment yield in these models include site topography, soil physical characteristics, soil moisture content, runoff, soil cover percentage, and supporting practice factors. The statistical model does not simulate soil erosion in a mechanistic or process-based way but takes into account rainfall intensity, slope, vegetation cover, soil texture, and depth to loamy layer in the field as predictors. Detailed information about the statistical model can be found in Raza et al. (2022), whereas the SIMPLACE model solutions are described in the following section (2.2.1).

2.2.1. Description of the SIMPLACE model solution

Two model solutions were developed to represent sediment yield in a daily timestep with the SIMPLACE framework. Each solution employed either Freebairn or Rose methods to represent soil erosion but shared the same structure for soil-plant-atmosphere processes, e.g.: SIMPLACE<Lintul5, SlimWater, Freebarin> and SIMPLACE<Lintul5, SlimWater, Rose>. In this way, the fraction of soil cover is dynamically simulated taking into account the green and senesced leaf area index (LAI) calculated by the Lintul5 module. Soil moisture is calculated based on soil water holding characteristics and atmospheric demand obtained by the Penman-Monteith and dual coefficient methods described in Allen et al. (1998). Both soil cover and moisture status are employed to calculate rainfall runoff, which in turn is an input for the erosion simulations with Freebairn or Rose method. An overview of the main interconnections across data inputs, model components, and variables to calculate sediment yield is provided in Fig. 4.3.

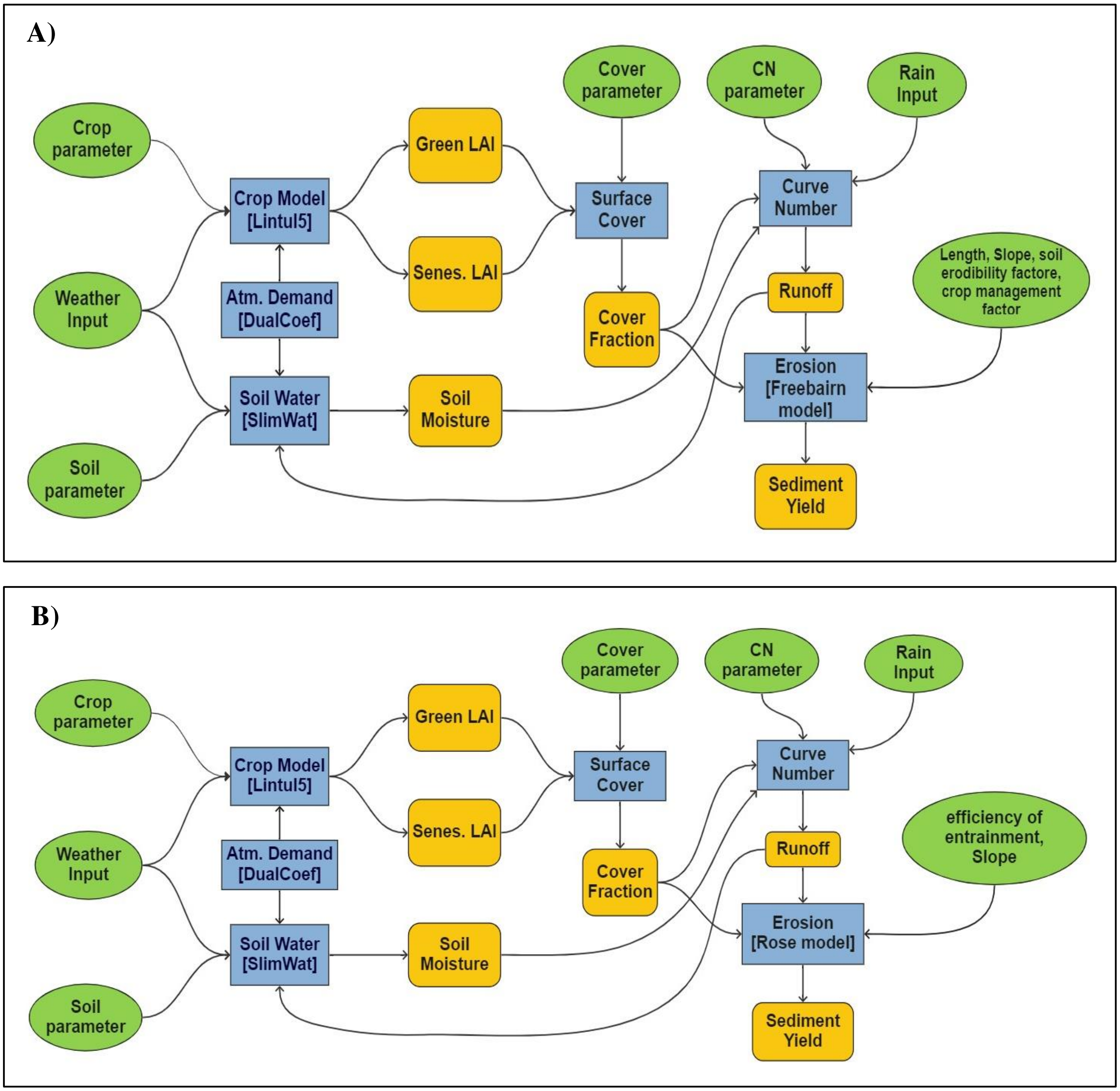


Fig. 4. 3: Simplified illustration of the model solutions developed for sediment yield in SIMPLACE (A) Freebairn model (B) Rose model. Green circles represent model input data and parameters, blue boxes are the modules within the SIMPLACE modeling platform, and orange boxes are the state variables.

2.2.2. Runoff

A SIMPLACE<RunoffCurveNumber_APSIM> component was implemented in this study following the same framework used in the widely used APSIM platform (Keating et al., 2003a). This component uses the soil cover fraction, daily rainfall, and soil moisture content to simulate the runoff volume according to the Curve Number approach (Munna et al., 2021). In addition, the calculations also consider the effects of surface organic matter deposited on the soil surface as described in the APSIM platform, which was originally adapted from the PERFECT model (Hajigholizadeh et al., 2018). Parameters describing the reduction of runoff due to surface residue (CNcov and CNred) and soil characteristic curve number (CN2) can be modified to represent different field conditions. The soil cover fraction is expressed by the Beer-lambert law as a function of LAI and surface organic matter.

$$Cover_{Green} = 1 - \mathrm{e}^{(-\mathrm{K_{Green}} * \mathrm{LAI_{Green}})} \tag{1}$$

$$Cover_{Senes} = 1 - \mathrm{e}^{(-\mathrm{K_{Senes}} * \mathrm{LAI_{Senes}})} \tag{2}$$

$$Cover_{SurfOM} = 1 - \mathrm{e}^{(-\mathrm{K_{SurfOM}} * \mathrm{SurfOM})} \tag{3}$$

$$Cover_{Total} = 1 - (1 - Cover_{Green}) * (1 - Cover_{Senes}) \tag{4}$$

The surface cover is estimated considering the surface organic matter using the add cover principle

$$CoverFraction = (1 - (1 - Cover_{Total}) * (1 - Cover_{SurfOM})) \tag{5}$$

Where LAI_{Green} is Green Leaf Area Index (m^2/m^2), LAI_{Senes} is Senesced Leaf Area Index (m^2/m^2), SurfOM (t/ha) is the soil surface residues; K_{Green}, K_{Senes}, and K_{SurfOM} are the extinction coefficients for green LAI, for senesced LAI and SurfOM, respectively.

Under the presence of soil cover, the CN2 value is internally adjusted to account for the runoff reduction due to surface residues and canopy interception. Surface residues inhibit the transport of water across the soil surface during runoff events and so the method uses a linear response curve to reduce runoff as a function of the amount of crop and residue cover. The effect on runoff is specified by a threshold surface cover (CN_{Cov}), above which there is no effect, and the corresponding curve number reduction (CN_{Red}) (Eqn. 6). A second step correction is applied to account for the preceding status of soil moisture, which scale a new CN value between dry and wet conditions of soil moisture in the top 45 cm soil depth (Eqn. 12 to 14). Runoff is then calculated with the corrected CN_{final} for soil moisture and soil cover conditions as shown in Eqn. 15-16.

Reduction in CN due to surface cover:

$$CN_{CoverRed} = min(\frac{CoverFrac}{\text{CNcov}} * CNred,\ CNred) \tag{6}$$

$$CN2 = (\max(0, \text{CN}_{\text{bare}} - CN_{CoverRed})) \tag{7}$$

Soil moisture factor:

$$FC_{frac[i]} = (SWC_{[i]} - WP_{[i]})/(FC_{[i]} - WP_{[i]}) \qquad \text{where } 0 \leq FC_{frac} \leq 1 \tag{8}$$

$$SF = 1/(1 - \exp(-4.16)) \tag{9}$$

$$pWeight_{[i]} = SF * (1 - \exp(-4.16 * \min(1,\ D_{[i]}\ /\ ED)) \tag{10}$$

$$CNSW_{fac} = \sum_{i=1}^{N} (FC_{frac[i]} * pWeight_{[i]}) \tag{11}$$

Where, SWC is the soil water content (m^3/m^3), FC is the field capacity (m^3/m^3), WP is the wilting point (m^3/m^3), $pWeight$ is a weighting factor as a function of soil depth, SF is the scaling factor used for $pWeight$, D is the depth of soil layer [i] and ED is the effective depth for which soil moisture exerts influence in runoff (e.g., 45 cm); CNSWfac is the integrated soil moisture factor for the runoff calculations.

Calculate CN at wet and dry conditions and scale with CNSWfac (Boughton, 1989):

$$CN_1 = (CN_2/(2.334 - 0.0133400 * CN_2)) \tag{12}$$

$$CN_3 = (CN_2/(0.4036 - 0.005964 * CN_2)) \tag{13}$$

$$CN_{final} = (CN_1 + (CN_3 - CN_1) * \text{CNSWfac}) \tag{14}$$

Where CNSWfac is soil water factor to correct CN

Potential max retention (s):

$$s = 254 * (\frac{100}{CN_{final}} - 1) \tag{15}$$

Runoff (Q):

$$Q = (P - a * s)^2/(P + (1 - \alpha) * s) \quad (16)$$

Where Q is runoff (mm), s is the retention parameter, P is depth of rainfall (mm), α is constant to correct rainfall after the start of runoff.

2.2.3. Crop growth and LAI dynamics (Lintul5)

The model component LINTUL5 is used in this study to simulate crop growth and LAI dynamics (Srivastava et al., 2016) including a module to simulate 1D root growth (SLIMRoots) (Seidel et al., 2022). In LINTUL5, daily temperature sums and crop-specific requirements are used to simulate the crop development stage (DVS) and progression from emergence (DVS = 0.0) to anthesis (DVS = 1.0) and maturity (DVS = 2.0). The model uses the concept of radiation use efficiency, which can vary throughout the crop's growth cycle and is depending on average air temperature and atmospheric CO_2 concentration. Potential biomass growth is reduced by low soil moisture, whereas the effects of atmospheric CO_2 concentration on radiation use efficiency and transpiration rates are detailed in (Oomen et al., 2016). Biomass is partitioned into roots, stems, leaves, and yield as a function of DVS, and water dynamics. Soil water is simulated by estimating daily changes in soil water content in a given number of soil layers based on the soil water balance approach. Evapotranspiration is calculated using a dual crop coefficient according to FAO56 methods (Allen et al., 1998). Soil temperature is simulated using methods from the APEX model (Gassman et al., 2010).

2.2.4. Soil erosion model approaches

2.2.4.1. Freebairn

A modified Universal Soil Loss Equation proposed by Freebairn and Wockner (Freebairn and Wockner, 1986) predicts soil erosion considering variations in soil loss with runoff volume and cover fraction. This approach uses MUSLE erodibility, slope length, and a support factor (Djoukbala et al., 2019).

The model has the following form:

$$SedConc = 16.52 - 0.46 * COV + 0.0031 * COV^2 \text{ (When Soil Cover < 0.5)} \quad (17)$$

$$SedConc = 2.54 - 0.0254 * COV \text{ (When Soil Cover >= 0.5)} \quad (18)$$

$$A = \frac{SedConc * LS * K * P * Q}{10} \quad (19)$$

Where A (t/ha) is the event soil loss, COV (%) is the cover fraction (e.g., *CoverFraction * 100*), LS is the slope length and steepness factor, K (dimensionless) is the soil erodibility factor, P (dimensionless) is the supporting practice factor (in this study set equal to 1), and Q (mm) is the event runoff. The 1/10 resolves the unit's conversion to obtain A in t/ha.

LS is a slope and length factor in USLE, is based on the equation (Presbitero et al., 1995),

$$\mathrm{LS} = (65.41 * \mathrm{S}^2 + 4.56 * \mathrm{S} + 0.065) * (\mathrm{L}/22.1)^m \quad (20)$$

$$m = 0.6 * (1 - e^{-35.835 * \mathrm{S}}) \quad (21)$$

LS is the slope length and steepness factor, S is sine of slope angle, and L (m) is the length of the catchment.

2.2.4.2. Rose model

The Rose model is a simplified sediment concentration function developed in 1985 (Rose, 1985). The equation is given as

$$E = 2700 * S * (1.0 - cover) * \lambda * \frac{Q}{100} \quad (22)$$

Where E (t/ha) is Event soil loss, S is sine of slope angle, cover (0-1) is fractional surface cover, Q (mm) Event runoff, and λ is factor approximating efficiency of entrainment.

The efficiency of entrainment λ is calculated as follows (Rose, 1985)

$$\lambda = \lambda_{bare} e^{-\beta * cov} \quad (23)$$

Where λ_{bare} the efficiency of entrainment of bare surface, COV (%) is surface cover. β is cover 'sensitivity' factor

2.3. Local statistical model

The locally developed sediment model ((Raza et al., 2022c) is a simple empirical model used to predict sediment yield as a function of Silt + OM (SiltOM), vegetation cover (VC), slope (S), rainfall intensity (RI), and depth to the loamy layer (DLL). The model is represented by the following equation

$$sediment\ yield = [-7.2 + 40.9SiltOM - 35.1VC + 46.9S + 58.6RI - 18.4DDL]/100 \quad (24)$$

Where Sediment yield is in t ha^{-1}. SiltOM, VC, Slope, RI, and DLL represent their levels.

2.4. Sensitivity analysis

A sensitivity analysis was performed for all parameters relevant to the sediment yield models to find the most influential parameters. The results were subsequently used to understand model behavior and guide calibration. To achieve this analysis, MUSLE model input factors were categorized into three groupings based on the MUSLE model structure: physical, conceptual, and hydrological input factors. Physical factors were length and slope, which were estimated by remote sensing and GIS. Conceptual factors were cover fraction and K, which were optimized through calibration, and the crop management factor which was assumed as 1 in this study. Hydrological factors were CN values for runoff estimation.

The global sensitivity analysis for model parameters was performed using Sobol2007 (Lucay et al., 2020). It applies the Monte Carlo estimation (Dagum et al., 2000) of Sobol's indices for both first-order and total indices at the same time. The effect of the model factor X_i on the output variance V can be described by the two Sobol's sensitivity indices: "Total sensitivity index (ST_i)" and "First order index (S_i)". ST_i expresses the ratio between the variance caused by the i_{th} factor when interacting with all the other model factors, while Si is calculated as the ratio between the variance directly caused by the i_{th} factor (V_i) and the total variance of the model output (V):

$$S_i = \frac{V_i}{V} \quad (25)$$

$$ST_i = 1 - \frac{V_{\sim i}}{V} \quad (26)$$

Where $V_{\sim i}$ is the variance not related to the i_{th} factor. ST_i considers all the possible interactions between model parameters, providing an understanding of the sources of uncertainties. Consequently, it is possible to prioritize the factors and exclude the non-sensitive (i.e. factors with low indices) from the further analysis of model calibration.

2.5. Model calibration and validation

2.5.1. Calibration procedure and setup

A classical approach was followed to: (a) evaluate model performance using statistical indexes of performance between the simulated and the observed values, and (b) adjust the parameters using an optimization algorithm. Root mean square error (RMSE) and Nash–Sutcliffe model efficiency coefficient (NSE) were used for model evaluation. An automatic calibration procedure with the Nelder-Mead method was implemented in Rscript to calibrate multiple parameters at the same time using the RMSE as the objective function. The procedure was reproduced several times considering different initial conditions to approximate the global minima. Maximum and minimum parameter values were imposed based on previous literature to select parameter values at plausible ranges.

2.5.1.1. Runoff and erosion

To calibrate the Runoff model, we used the observed runoff data from rainfall simulator field experiments conducted at different crop stages of winter triticale from September 2020 to February 2021 (Table 4.2). Model fit was optimized also using the RMSE and NSE values between the dataset of field observations and the model results. The important parameter is the runoff curve number (Hawkins, 1996) at bare field cover, used in partitioning rainfall between infiltration and runoff, which is usually derived from guidelines based on soil texture and soil surface characteristics (Ringrose-Voase et al., 2003). Under high spatial heterogeneity of soil characteristics, CN_{bare} was calibrated to obtain the optimum CN_{final} that represents all the 16 points distributed across the field.

The selected erosion models were calibrated with the data set from the field experiments for sediment yield at different crop stages of winter triticale between September 2020 and February 2021. Both Freebairn and Rose erosion models calibration were done separately for all sampling points. Soil erodibility factor K was calibrated for the Freebairn model to find the best suitable value for K that represents the spatial heterogeneity across all sampling points. The same procedure was applied to calibrate the efficiency of the entrainment factor for bare surface (λ_{bare}) in the Rose model. While by definition $0 < \lambda_{bare} < 1$, at present λ can only be determined accurately by calibrating the model against measurement data on sediment concentration. Values of λ_{bare} depend on soil type, and field management practices. As the factor λ plays an important role in the performance of the Rose model, we calibrated the λ_{bare} for further analysis. Parameter values obtained on the field experiment in 2020-2021 were used for the calibration of soil erosion models and observed field data collected betrween September 2021 and November 2021 were used for the validation of the models (Table 4.2).

2.5.1.2. Lintul5

Lintul5 crop parameters were calibrated (1) for the winter triticale cropping season in 2019-2020 and (2) for the rapeseed cropping season in 2021-2022 (Table 4.2). The data used for calibration was the phenological stage, LAI, and total aboveground biomass collected at different times within the growing season. The first step consisted of adjusting the phenological parameters TSUM1 and TSUM2 to match the observed data. Then, the parameters controlling the "crop radiation use efficiency and specific leaf area" were adjusted to calibrate LAI and aboveground simulations. A third step consisted in adjusting the maximum rooting depth, necessary to better represent the crop response to drought. The parameters for calibration of Lintul5 were selected based on the literature review for winter wheat growth simulation (Asseng et al., 2013). As the observed data for rapeseed were collected in only one cropping season, the crop model (LINTUL5) was calibrated with the half dataset of crop observation points in the season, whereas the other half was used to validate the model for rapeseed growth. The base parameter values used as the starting point to calibrate Lintul5 for both crops were those used by (Webber et al., 2020) to simulate winter wheat and rapeseed across Germany.

2.5.2. Validation

Validation for runoff and sediment yield was performed by assessing the fit of models to the observed data collected from the field experiments in September and November 2021 during the rapeseed crop growing season. The crop model (LINTUL5) was also validated for the winter triticale data observed in 2020-2021 (Table 4.2). The validation of the crop model was performed with half the dataset observed for rapeseed crop in 2022 to support the performance of runoff and erosion models in rapeseed crop cover (Table 4.2).

3. Results and discussion

3.1. Sensitive parameters and input information for the erosion models

The sensitivity analysis presented consistent results regarding the importance of the input data on runoff volume and slope angle for both the Freebairn and Rose erosion models. The simulations of sediment yield from the Rose model showed a sensitivity to the cover fraction between 0% and 25% compared to that of the Freebairn model (Fig. 4.4a). The selected parameters with the highest influence were used for model calibration (Table. 4.3). Soil erodibility factor K was the highest influential parameter after slope angle for Freebairn model. The values of the Sobol indices for other parameters which were used as observable inputs, identified the importance of the quality of collected input data. The most significant change in sensitivity for the Freebairn model occurred in the vegetation cover transition from 0% to 50% (Fig. 4.4b). The interception of rainfall by the vegetation cover is low with less vegetation cover and hence raindrops are reaching the soil surface with higher kinetic energy. In a field, with sandy topsoil textures causing a high soil erodibility factor K presents a higher sediment yield (Bonilla and Johnson, 2012). On the other hand, the ranking of the sensitivity of the parameters changed for the Rose model (Fig. 4.4a). The λ_{bare} was the most influential parameter in the Rose model. The changes in sensitivity of the parameters of Rose model occurred within a small range of vegetation cover i.e. in the transition from 0% to 25% cover. This may represent a limitation in the applicability of the Rose model at higher vegetation cover (Silburn, 2011). Entrainment by the surface flow is thus the dominant mechanism contributing to sediment transport in the Rose model when vegetation cover is small (Rose, 1985).

Table 4. 3. Ranking of parameters

Model	Parameter	Ranking	Range for sensitivity	
			Min	max
Freebairn	Slope angle	1	0.01	45
	K	2	0.01	0.3
	Q	3	1	25
Rose	λ_{bare}	1	0	1
	Q	2	1	25
	Slope angle	3	0.01	45

Slope angle: degrees of slope in the field (degree), K: soil erodibility factor, Q: surface runoff (mm)

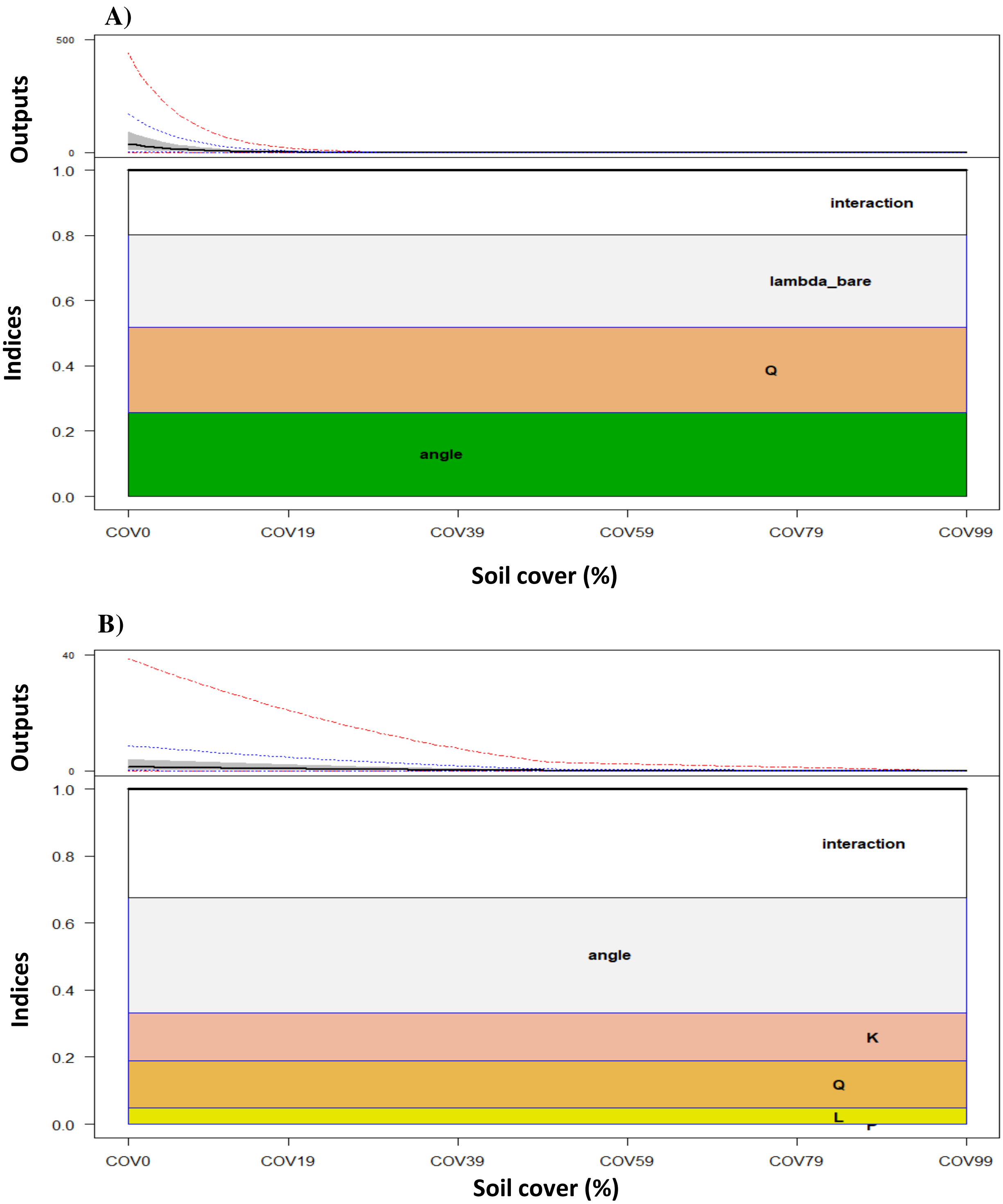


Fig. 4. 4*:* **Evolution of the Sobol sensitivity indices of the (A) Rose and (B) Freebairn model parameters from cover = 0 % to cover = 100%. The upper subplot shows the extreme (colored dashed -lines), inter-quartile (grey), and median (bold line) output values of soil erosion at all cover steps. The lower subplot represents the sensitivity indices at all cover steps for the main effects and the first-order interactions.**

3.2. Calibration results

The ranges of values of the parameters used for calibration and the final calibrated values are shown in Table 4.4.

Table 4. 4. The ranges of values of the parameters used for calibration

Model	Parameter	Calibration range		Calibrated value	Uncalibrated value
		min	max		
Runoff					
	CN_{red}	5	20	6.44	20
	CN_{bare}	61	85	83.99	80
	α	0.05	0.3	0.05	0.2
Rose					
	λ_{bare}	0.1	1	0.20	0.7
	β	0.01	0.5	0.04	0.15
Freebairn					
	K	0.15	0.4	0.2	0.3

CN_{red}: CN value at residue cover, CN_{bare}: CN value at bare land, λ_{bare}: efficiency of entrainment at the bare surface, β is cover 'sensitivity' factor, K: soil erodibility factor

3.2.1. Runoff

Simulation of daily runoff during the growing season is shown in Fig. 4.5. The comparison of runoff volumes observed in the field during the measurements with the rainfall simulator and the simulated values is shown in Fig. 4.6.

After calibration of the model on the 16 observation points, the average curve number for the soil with no vegetation cover ($CN_{bare,}$ in Eqn. 7) was 83.9, the value of CN_{red} was 6.4 and α was 0.05. Before calibration, the standard CN method underestimated the runoff depths for all 16 plots with RMSE and NSE of 10.34 mm and -0.06 respectively (Fig. 4.6b). Similar underestimation was reported by (Van Mullem, 1991) suggesting that multiple factors might cause this underestimation of runoff depth, but the soil cover and moisture are considered one of the most influential factors which affect the values for CN and α for initial abstraction (Littleboy et al., 1996). (Huang et al., 2007) evaluated that tabulated CN values are almost always lower than that of measured CN values which results in underestimated runoff depths. These observations by (Huang et al., 1999) that the underestimation of runoff depth by the standard SCS method is due to underestimating the CN_{final} with the available soil moisture content value, which results in underestimated runoff. However, the value of α for initial abstraction could be calibrated to improve the runoff predictions. A comparison of Fig. 4.6a and Fig. 4.6b indicates that runoff estimations are in better agreement with observed runoff measurements with α value of 0.05. Based on the calibration results, the used α value as 0.05 would be appropriate rather than the commonly used value of 0.2. This increased the model NSE from -0.06 to 0.89 compared to the uncalibrated CN approach. This agrees with findings by (Shi et al., 2009), who showed that modified α and CN_{bare} values improved the agreement between measured and predicted direct runoff to a high degree.

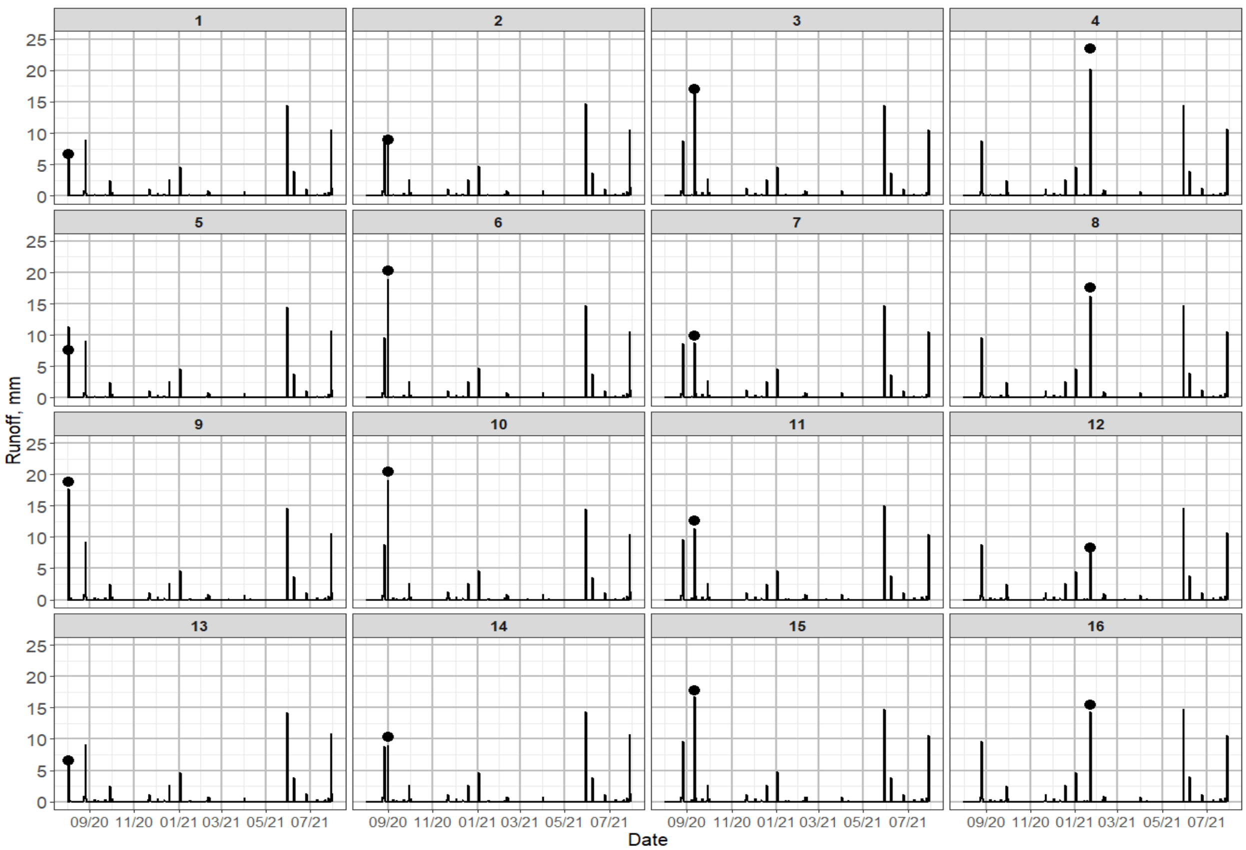


Fig. 4. 5: Simulation of Runoff during the cropping season 2020-2021 of Winter Triticale after calibration on 16 distinct points in the field where rainfall simulator experiments were conducted between September 2020 and April 2021 (see black dots in each figure)

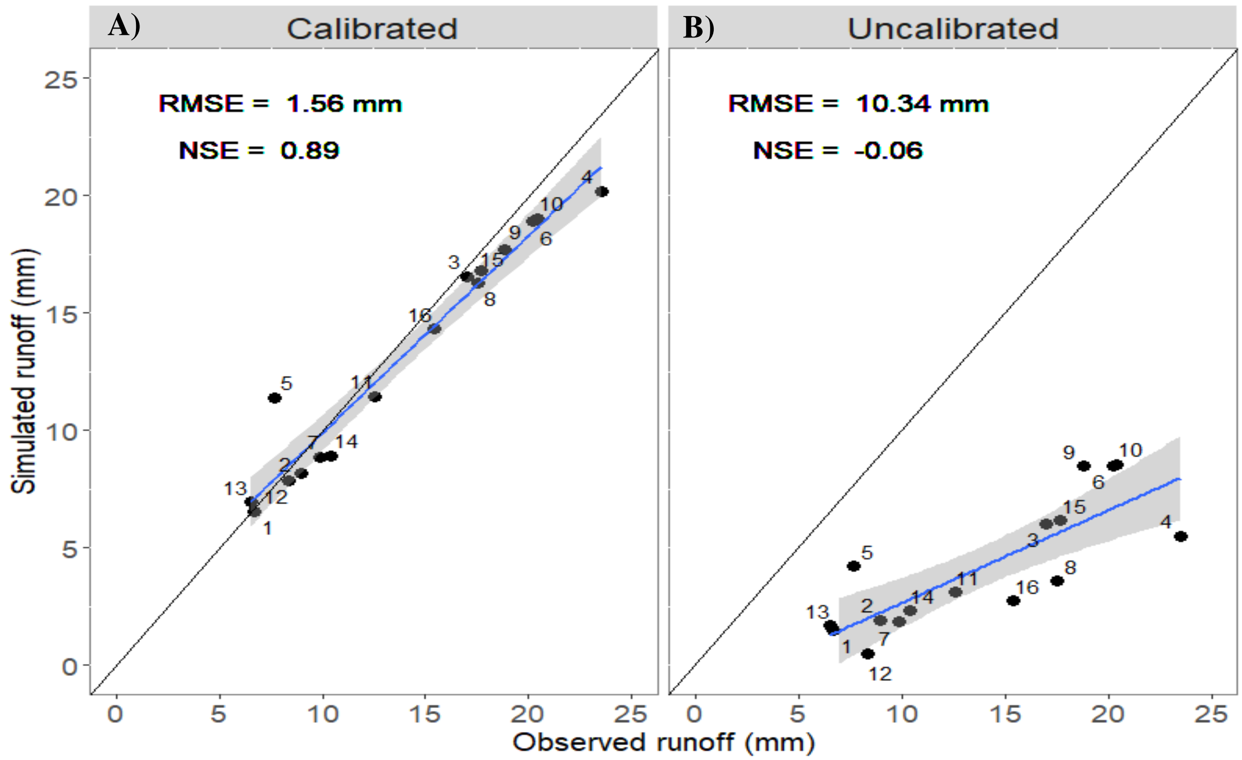


Fig. 4. 6: Comparison of observed and simulated runoff with calibrated (A) and uncalibrated (B) parameter values

3.2.2. Performance of the Erosion models

Simulation of daily sediment yield during the growing season 2020-2021 by the Freebairn and Rose models are shown in (Fig. 4.7 & 4.8) for the calibration. The comparison of observed and simulated values along the 1:1 line for calibration is shown in (Fig. 4.9, 4.10 & 4.11).

Soil erosion observation results showed that higher rainfall intensities produce more runoff and sediment yield in each event with 0 % vegetation cover expressed by an LAI of 0 (Table 4.5). The highest rate of erosion was estimated in plot 10, where the simulated soil loss was 4.39 and 4.11 t ha^{-1} d^{-1} by Freebairn and Rose models, respectively, whereas the local statistical model predicted the highest soil loss of 4.19 t ha^{-1} d^{-1} at plot 9.

Table 4. 5. Simulated sediment yield and runoff resulting from event rainfall simulations in 2020-2021 on 16 experimental rainfall simulator plots

Test Plot	Slope %	K	Measured LAI m^2/m^2	Applied rainfall mm	runoff mm		Simulated sediment yield $t\ ha^{-1}\ d^{-1}$			
					Observed	Simulated	Observed	Freebairn	Rose	Local model
1	1.48	0.30	0.01	16.24	6.71	6.55	0.64	0.43	0.54	0.86
2	2.9	0.33	0	18.72	8.97	8.15	1.26	0.93	1.02	1.38
3	3.1	0.34	0.15	29.88	17.01	16.55	1.88	1.73	1.64	1.90
4	4.8	0.37	0.2	35.52	23.50	20.19	2.16	1.57	0.86	2.42
5	3.8	0.29	0.1	22.9	7.67	11.39	2.07	2.05	2.39	2.36
6	1.79	0.32	0	32.4	20.22	18.90	2.93	1.29	1.46	2.31
7	4.78	0.33	0.15	19.96	9.85	8.87	1.51	1.63	1.35	1.79
8	3.3	0.35	0.2	30.72	17.53	16.28	1.98	0.78	0.48	1.74
9	4.07	0.31	0.1	30.72	18.80	17.69	3.71	3.49	3.98	4.19
10	5	0.29	0	32.56	20.44	19.03	4.99	4.39	4.11	3.90
11	2.47	0.25	0.15	23.44	12.57	11.46	1.73	0.93	0.91	1.01
12	2.23	0.27	0.2	19.44	8.34	7.87	0.60	0.24	0.16	0.72
13	8.02	0.34	0.1	16.8	6.54	6.93	3.23	3.60	3.07	3.71
14	4.65	0.28	0	19.8	10.38	8.92	2.50	1.86	1.79	2.12
15	4.36	0.25	0.15	30.2	17.69	16.82	3.62	2.73	2.35	3.61
16	2.57	0.31	0.2	28.24	15.41	14.32	1.19	0.51	0.33	2.02

In Fig. 4.7, simulated sediment yield by the Rose model tends to match with observed data except for the points where the slope is small without vegetation cover (Plot 6) and where the slope is steep and LAI is around 0.2 (plots 8, 12 and 15) regardless of the rainfall intensity (Table. 4.5, Fig. 4.7). Similarly, the simulated sediment yields with the Freebairn model were underestimated on these plots (Fig. 4.8). The local statistical model, on the other hand, shows better agreement between observed and predicted sediment yields (Fig. 4.11). Rose and Freebairn models produced relatively similar predictions, however, the Freebairn model showed a slightly better accuracy of erosion estimations among plots having significant soil characteristics variations among these test plots. The Freebairn model was quite sensitive to the erodibility factor K, which explains the high underprediction of the sediment yield in plot 6 and plot 8 (Fig. 4.8) when the calibrated value of 0.2 compared to the measured values of K as 0.32 and 0.35 respectively for these plots was used (Table 4.5). The K factor is controlled by intrinsic soil properties such as texture and is also influenced by more dynamic soil properties such as soil moisture content, aggregation, and SOM (Marques et al., 2019; G. Wang et al., 2016; Webb and Strong, 2011). However, these studies were specific to local soil conditions and for a given area. Relationships among the soil properties and the soil erodibility indicator K in the rainfall experiment using Pearson's correlation coefficients were calculated for the local application (Table 4.6). The results showed that the SOM contents (R = −0.48) were negatively correlated with soil erodibility, which suggested that erodibility is highly controlled by SOM. However, the current definition of the Freebairn K factor does not take these relationships into account. These results are consistent with the findings of (Stanchi et al., 2015) that erodibility is negatively correlated with organic content within the range of 0 to 10%.

Table 4. 6. Pearson's correlation coefficients (R) between soil properties variables for all rainfall simulation samples

	Slope %	SOM %	SAWHC[1] mm	Sand %	Silt %	Clay %	Topsoil layer moisture content mm	Bulk density kg m^{-3}	K
Slope	1								
SOM	-0.11	1							
SAWHC*	-0.42	-0.02	1						
Sand	0.18	0.14	-0.4	1					
Silt	-0.05	-0.32	0.37	-0.89	1				
Clay	0.22	0.11	0.02	-0.77	0.69	1			
Topsoil layer moisture content	-0.13	-0.51	-0.19	-0.01	0.19	0.02	1		
Bulk density	0.56	0	-0.24	0.19	-0.14	0.07	-0.31	1	
K	0.24	-0.48	0.09	-0.43	0.7	0.43	0.47	-0.08	1

[1]SAWHC: soil available water holding capacity

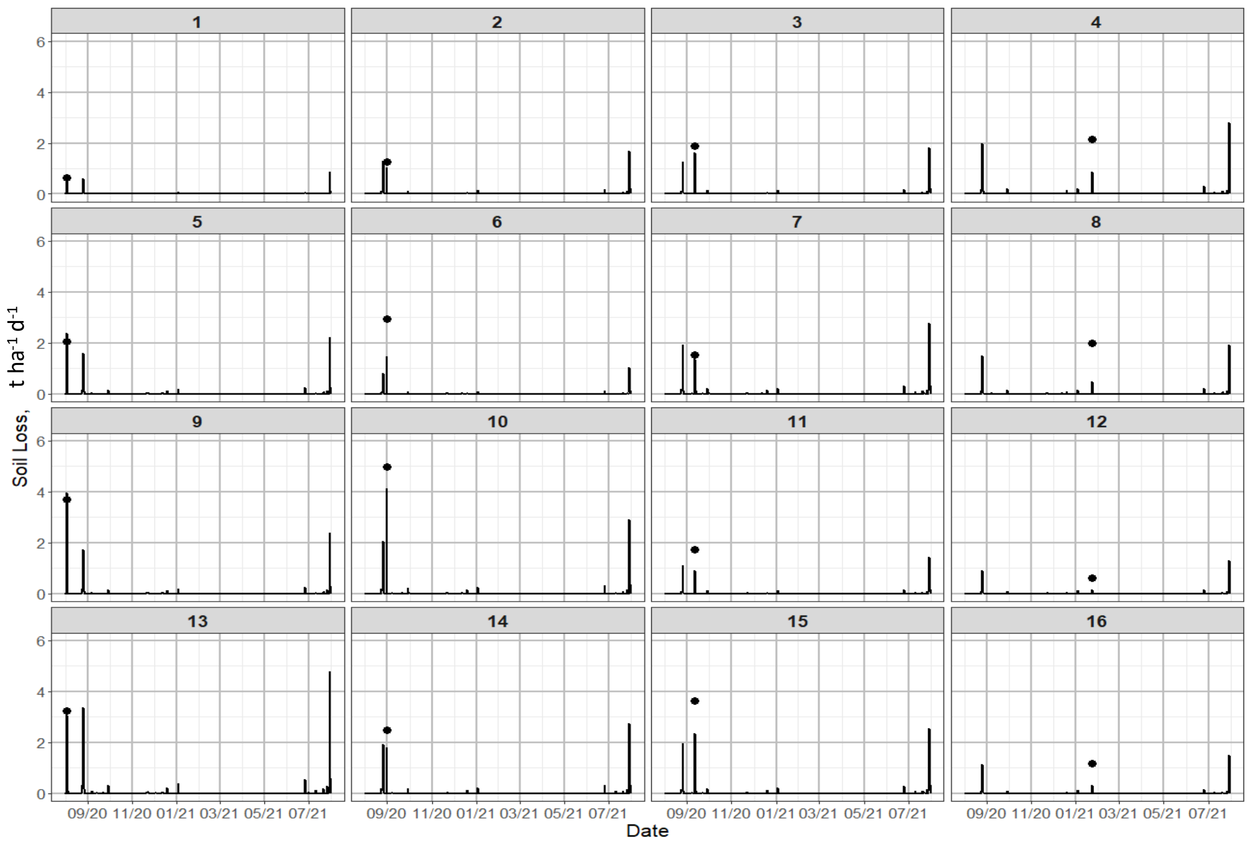


Fig. 4. 7: Sediment yields of Rose model simulation after calibration during the cropping season 2020-2021 of Winter Triticale. SAWHC*: Soil available water holding capacity; SM*: Soil moisture content before the experiment

The Rose model showed clear underprediction for the plots with LAI higher than 0.15 in plots 4, 8, 12, and 16 (Fig. 4.7). The LAI simulation results for calibration are presented in Fig. 1 in Appendix.The performance of the Rose model depends on the λ which relies on soil type, management, and the fraction of soil surface exposed to overland flow (Rose et al., 1983). The value of λ for high vegetation cover was considerably lower (Table. 1). (Silburn, 2011) suggested that λ is in reverse relation with a cover fraction which is also evident in this study where λ is negatively correlated with cover (-0.93) (Table. 4.7). Moreover, lower λ values for cultivated soils are related to their erodibility leading to low sediment yield with high runoff amounts at plot 6 (Fig. 4.7) (Table. 4.1) which agrees with reports by (Silburn, 2011).

Table 4. 7. Pearson's correlation coefficients (R) between soil properties and cover for all rainfall simulation samples

	Slope	SOM	sand	silt	clay	Bulk density	cover	λ
Slope	1							
SOM	-0.11	1						
sand	0.18	0.14	1					
silt	-0.05	-0.32	-0.89	1				
clay	0.22	0.11	-0.77	0.69	1			
Bulk density	0.56	0	0.19	-0.14	0.07	1		
cover	-0.15	-0.38	0.34	-0.21	-0.51	-0.43	1	
λ	0.07	0.34	-0.24	0.14	0.5	0.41	-0.93	1

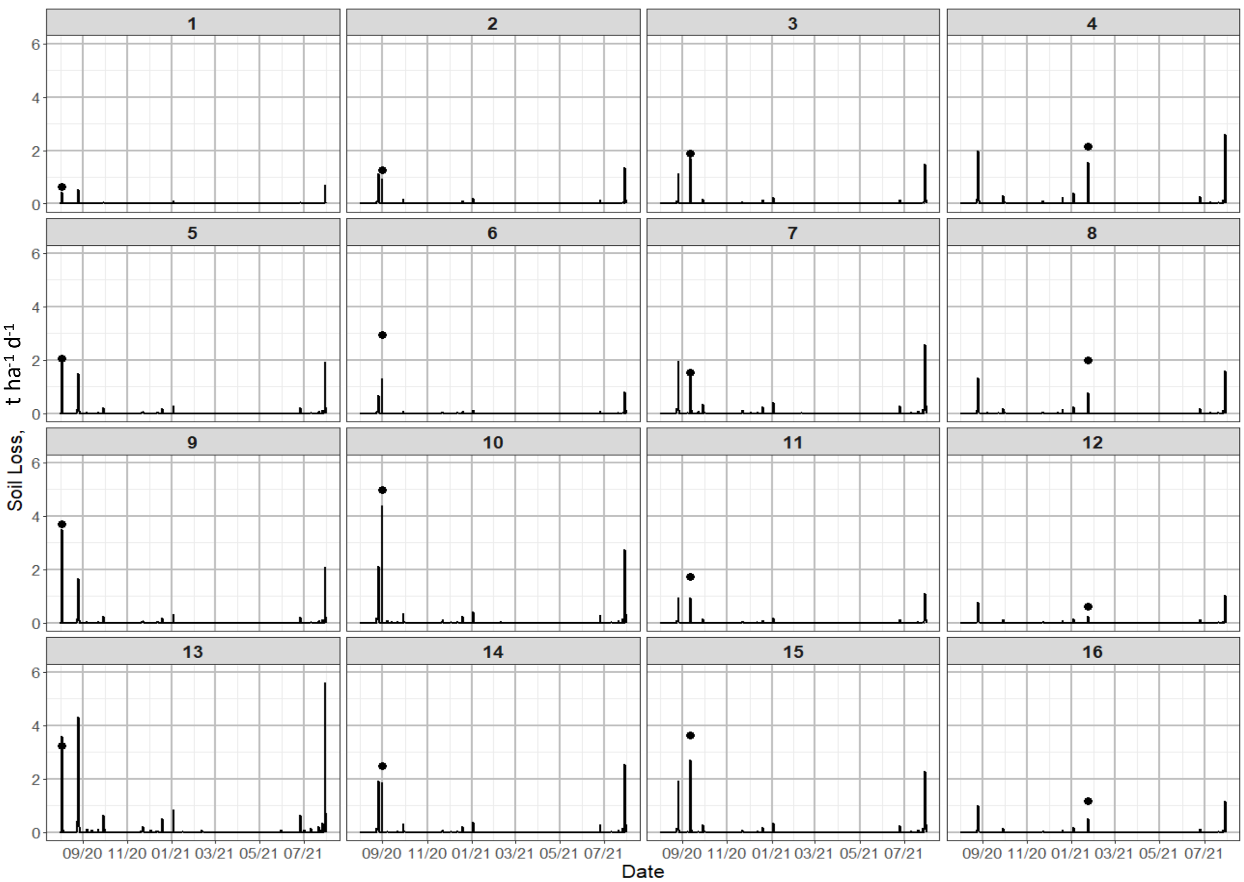


Fig. 4. 8: Sediment yields produced by the Freebairn model simulations after calibration during the cropping season 2020-2021 of Winter Triticale

The simulated sediment yields were close to the observed values (Fig. 4.9, 4.10, 4.11) showing that all three models had a positive relationship between estimated and observed sediment yield. The local statistical model showed the highest accuracy with NSE = 0.82. However, the performance parameters of dynamic model simulation of the Freebairn and Rose models showed that the Freebairn model more accurately estimated the sediment yield compared to predictions made by the Rose model. The Freebairn model predicted sediment yield with NSE = 0.71 and RMSE = 0.69 which is better than the model efficiency of Rose (NSE= 0.62, RMSE = 0.83). This value of model efficiency is satisfactory for sediment yield calibration as reported by (Onsamrarn et al., 2020). When Rose and Freebairn models were run with calibrated lintul5, sediment yield predictions were slightly lower in efficiency (Fig 4.9a, Fig. 4.10a) compared to the predictions when models were run with an observed cover fraction (Fig. 4.9b, Fib. 4.10b). Disagreement in predictions tended to increase when models were run with calibrated runoff model and uncalibrated lintul5 (Fig. 4.9c, Fig, 4.10c). However, the errors in sediment yield for both models were drastic when models were run with calibrated Lintul5 only as evident from NSE values of -0.13 and -0.1 for Freebairn and Rose models respectively (Fig. 4.9d, Fig. 4.10d). Similar trend in NSE was found with uncalibrated runoff and lintul5 models (Fig. 4.9e, Fig, 4.10e).

These results showed that a performance assessment of the runoff model is important to accurately predict the sediment yield with Freebairn and Rose models within SIMPLACE. This is also evident from the correlation coefficients between erosion models and cover with -0.01 and -0.14 for Freebairn and Rose models respectively, whereas, there is a strong positive correlation with runoff (Table. 4.8). This was explained in the study by (Raza et al., 2022b) where Rainfall intensity contributed most strongly to sediment yield (40.55%) followed by slope steepness (23.76%) and vegetation cover (17.73%). (Panagos and Katsoyiannis, 2019; Peng and Wang, 2012) indicated that sediment yield was positively related to the runoff events with high rainfall storms.

Table 4. 8. Pearson's correlation coefficients (R) between output variables produced by different erosion, runoff, and vegetation models for all rainfall simulation tests

	Slope	Lintul5 LAI	Applied rainfall	USDA runoff	Freebairn	Rose	Local model
Slope	1						
Lintul5 LAI	0.11	1					
Applied rainfall	-0.05	0.46	1				
USDA runoff	-0.03	0.42	0.99	1			
Freebairn	0.74	-0.01	0.26	0.32	1		
Rose	0.61	-0.14	0.21	0.29	0.97	1	
Local model	0.68	0.04	0.44	0.49	0.92	0.89	1

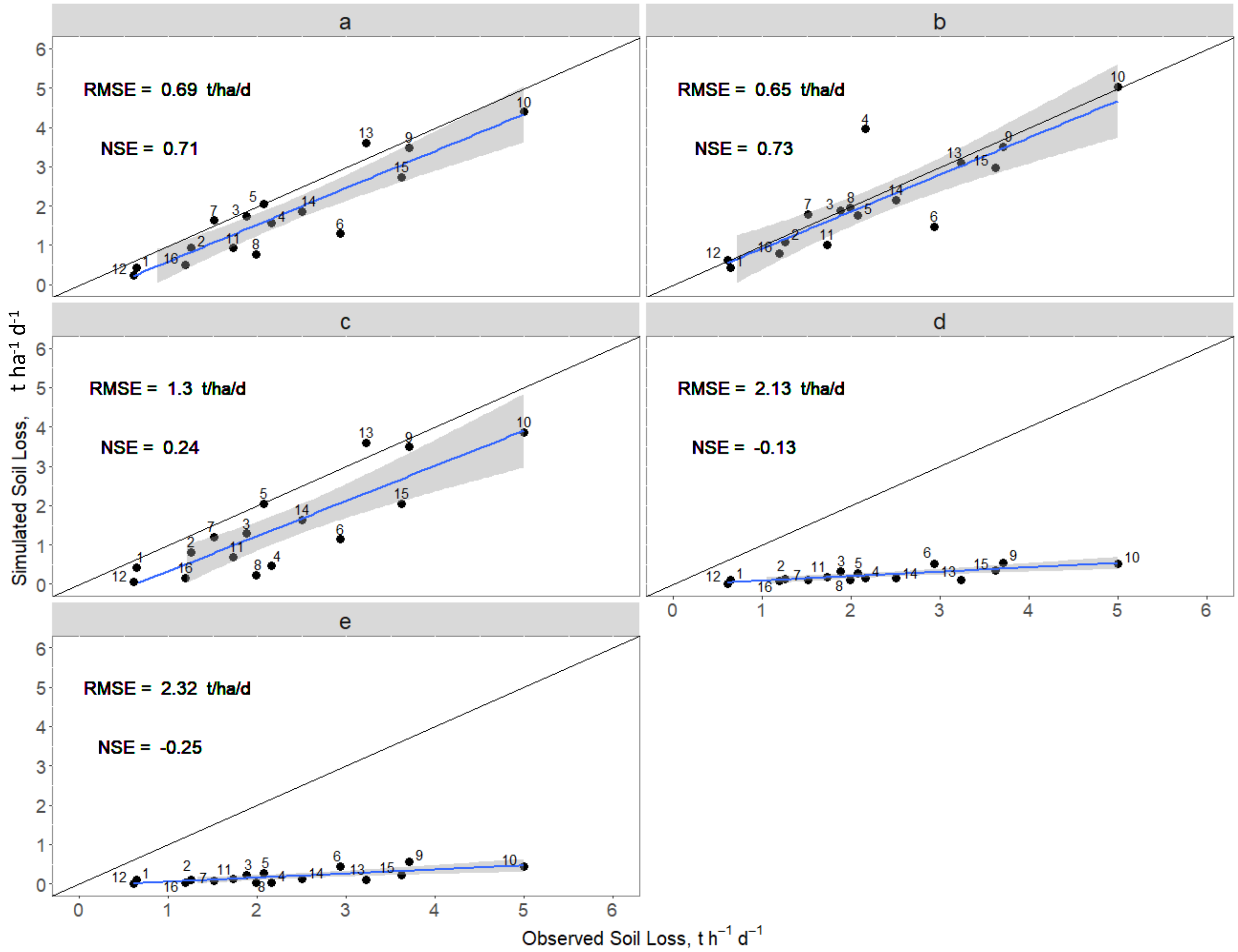


Fig. 4. 9: 1:1 line relationship between simulated and observed sediment yield for the calibration of the Freebairn. When Freebairn model; (a) calibrated with pre-calibrated Lintul5 & runoff models, (b) Calibrated with observed LAI and pre-calibrated runoff, (c) Calibrated with pre-calibrated runoff model only, (d) Calibrated with pre-calibrated Lintul5 only, (e) Calibrated with uncalibrated Lintul5 and runoff models

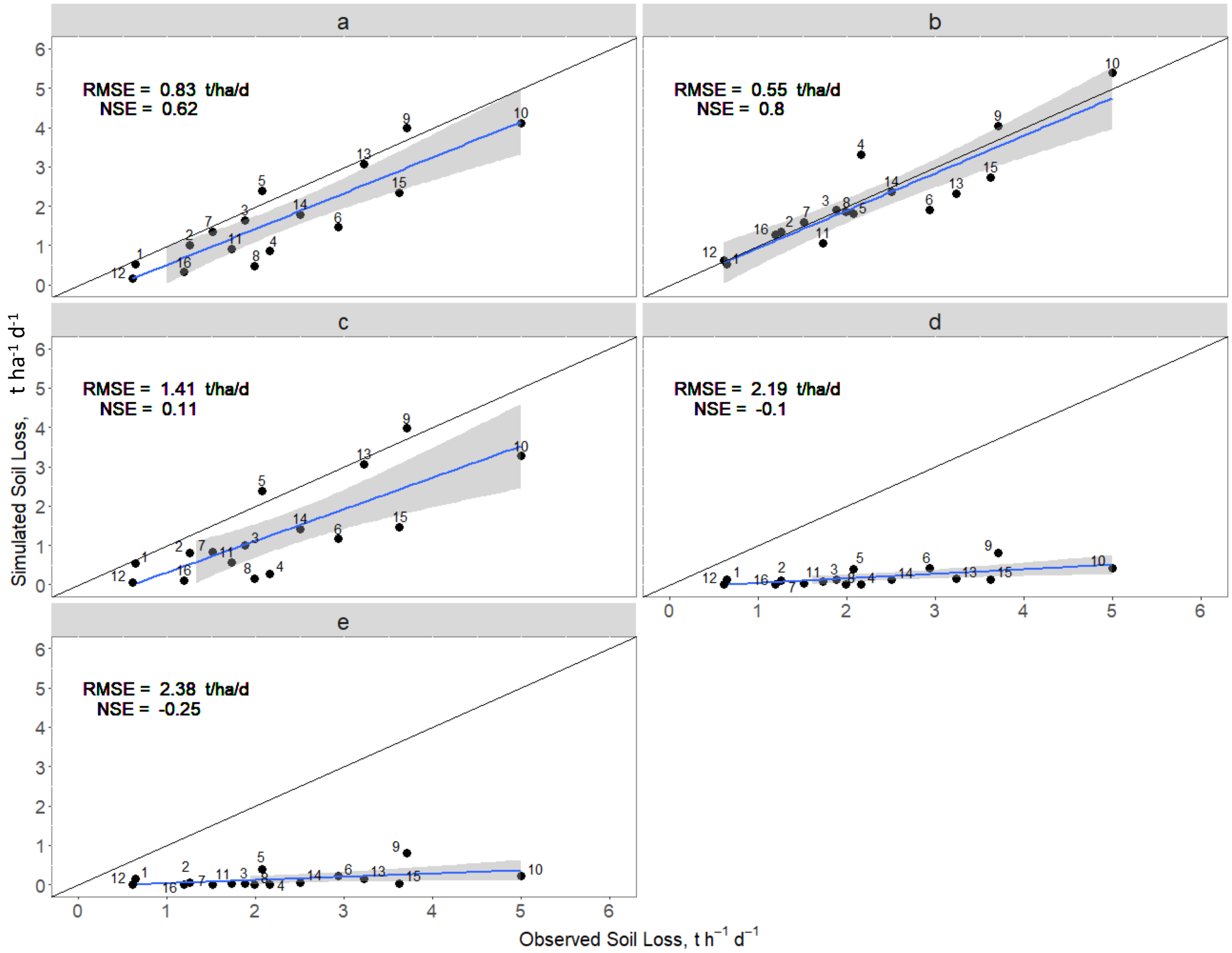


Fig. 4. 10: 1:1 line relationship between simulated and observed sediment yield for the calibration of the Rose model. When Rose model; (a) calibration with pre-calibrated Lintul5 & runoff models, (b) Calibrated with observed LAI and pre-calibrated runoff, (c) Calibrated with pre-calibrated runoff model only, (d) Calibrated with pre-calibrated Lintul5 only, (e) Calibrated with uncalibrated Lintul5 and runoff models

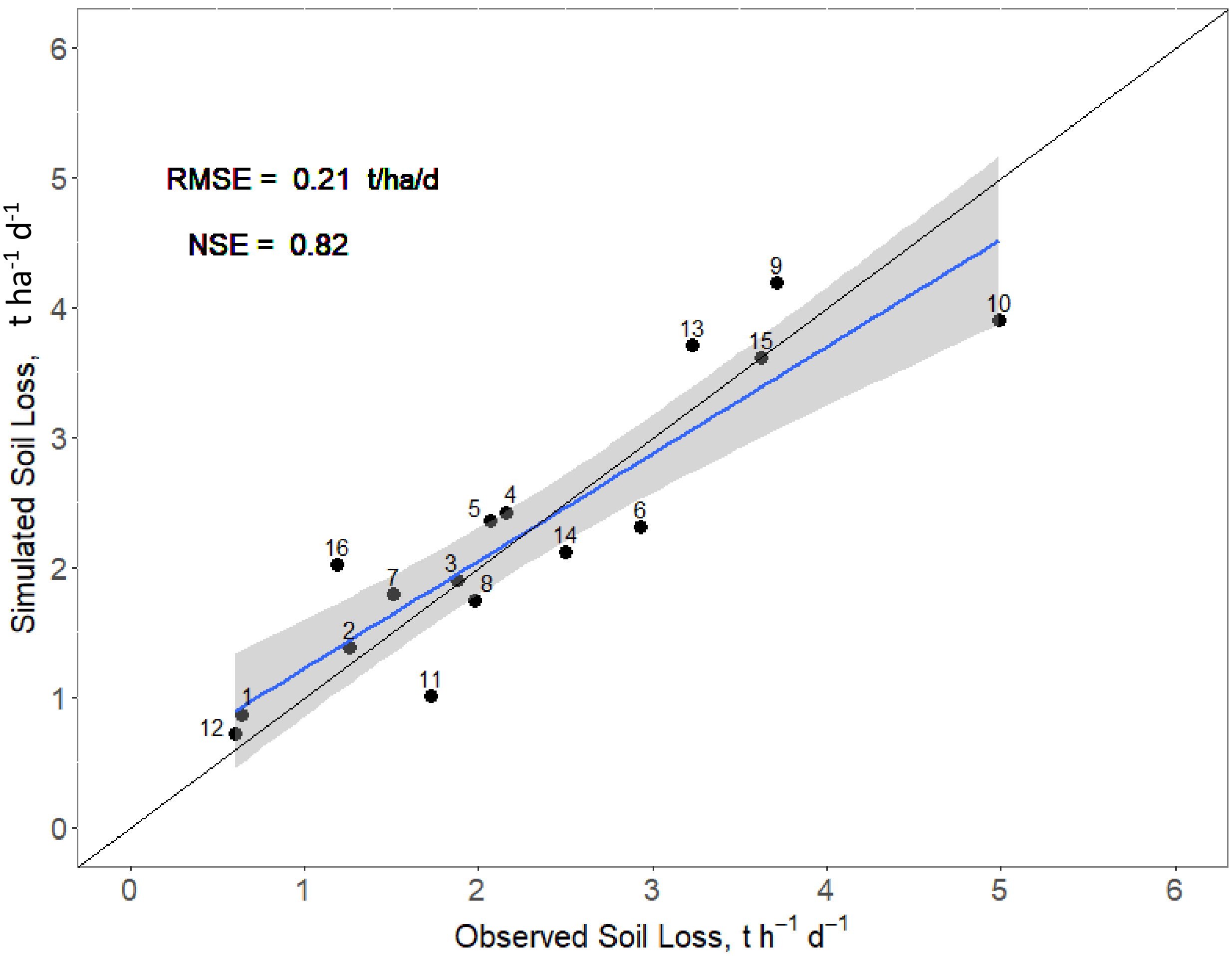
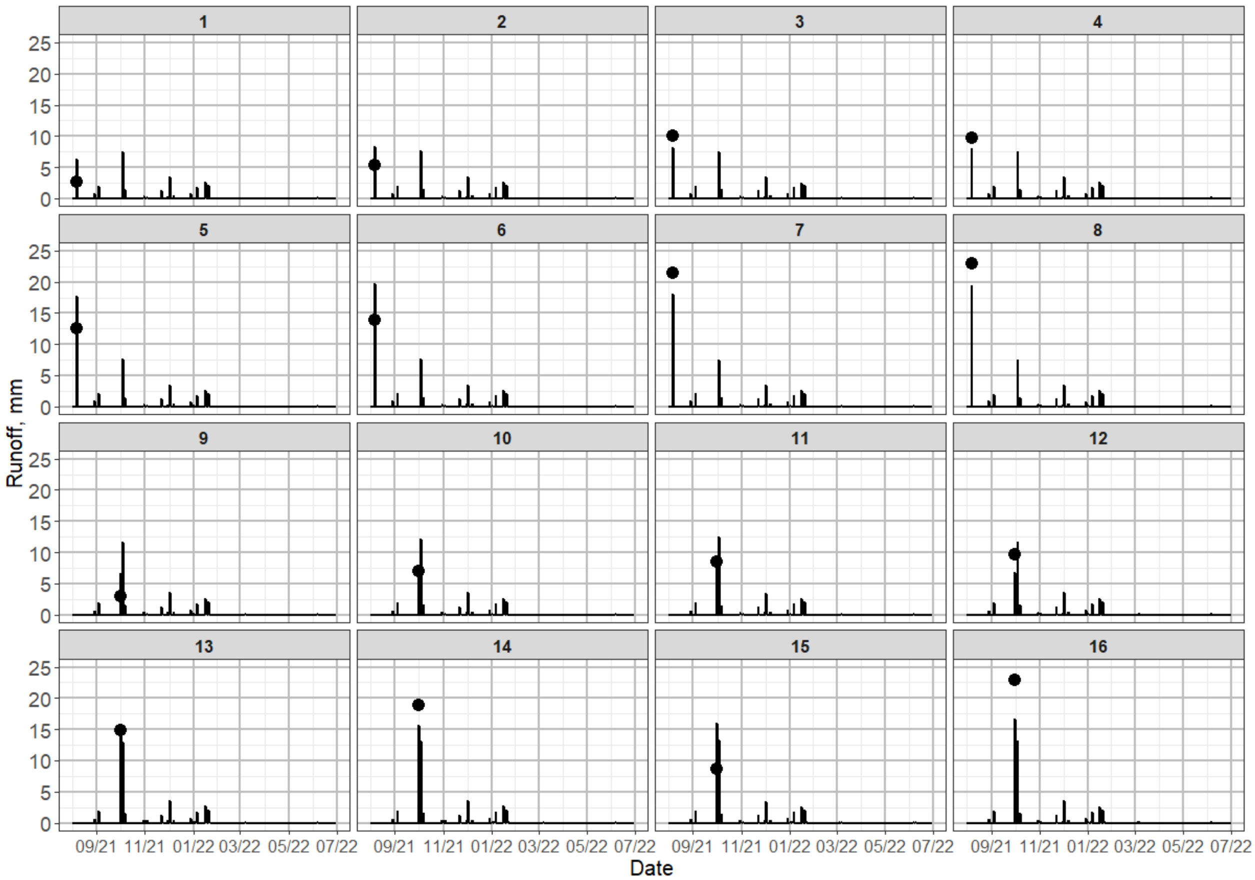


Fig. 4. 11: 1:1 line relationship between simulated and observed sediment yield for local model

3.3. Validation

An attempt was made to validate the runoff model after the calibration with data from September 2021 to November 2022 rapeseed cropping season. The LAI simulation results for validation are presented in Fig. 2. in Appendix. The simulation results showed that RMSE values of runoff with the validation data set (Fig. 4.12b) were slightly higher than after calibration (Fig. 4.6a). Nevertheless, many tested models have difficulties in simulating the runoff at extremely low and high rainfall events. (Chahinian et al., 2005) investigated that this problem is caused by difficulties in determining the soil moisture conditions during flood events, which do not necessarily consider the soil moisture distribution during the duration of the rainfall events.

A)



B)

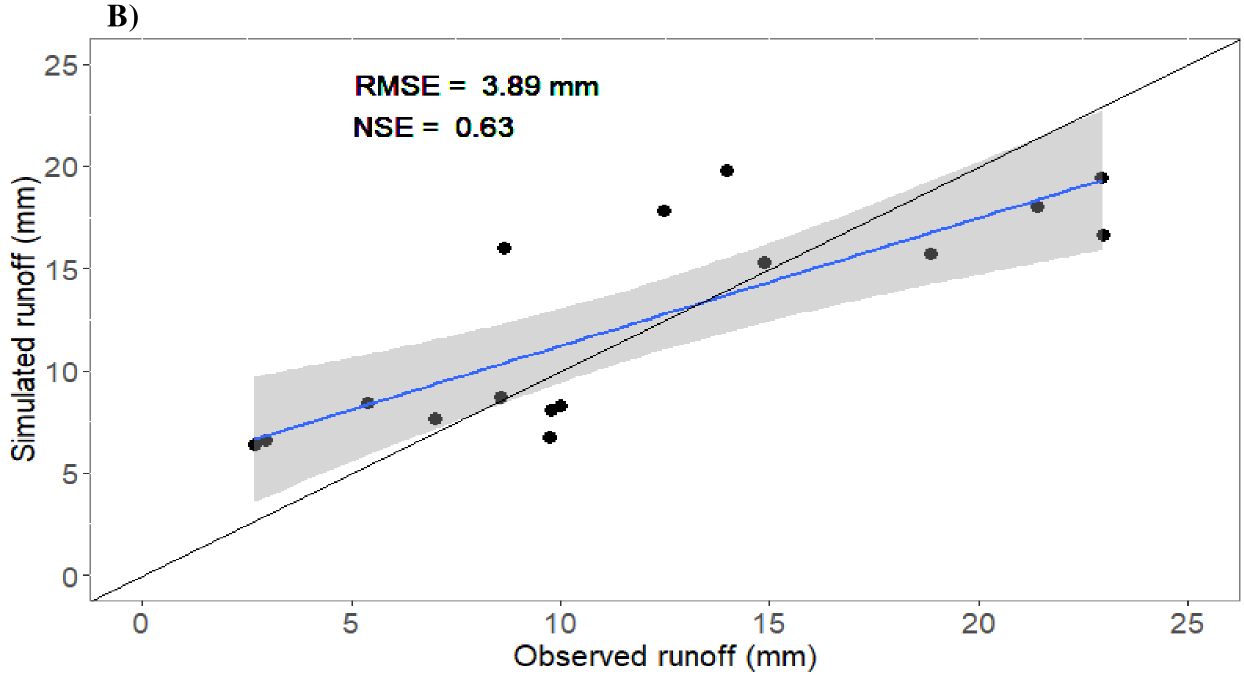


Fig. 4. 12: Validation of the runoff model during the cropping season 2021-2022 on 16 distinct points in the field (A) where rainfall simulator experiments were conducted between 2021 and 2022 (see black dots in each figure) (B) 1:1 line relationship between simulated and observed runoff yield during the validation period

Simulation of daily sediment yield during the growing season 2020-2021 by the Freebairn and Rose models are shown in (Fig. 4.13a & 4.14a) for validation. The comparison between the simulation and observed values along the 1:1 line for validation is shown in (Fig. 4.13b, 4.14b & 4.15). Both Freebairn and Rose models performed well (Fig. 4.13b & 4.14b) when the runoff model efficiency indicator was acceptable (Fig. 4.12b). Results of the validation assessment of erosion models showed that the Freebairn model had a good performance in sediment yield predictions during the validation period (Fig. 4.13b). In contrast, the Rose model had a limitation in sediment yield prediction and showed slightly higher RMSE (0.89 t ha^{-1} d^{-1}) and NSE (0.8) under the highly heterogeneous soil conditions of the experimental site (Fig. 4.14b). The λ values from the rainfall simulator plots may tend to underestimate soil loss on longer slopes and overestimates on high rainfall intensity events (Silburn, 2011). The performance of the local model with the validation data set, on the other hand, showed the highest uncertainties in simulating sediment yield with an RMSE value of 1.1 t $ha^{-1}d^{-1}$ among erosion models in this study (Fig. 4.15). This is because of the specific environmental conditions (soil physical characteristics, topography, and vegetation cover) during the development of the local statistical model.

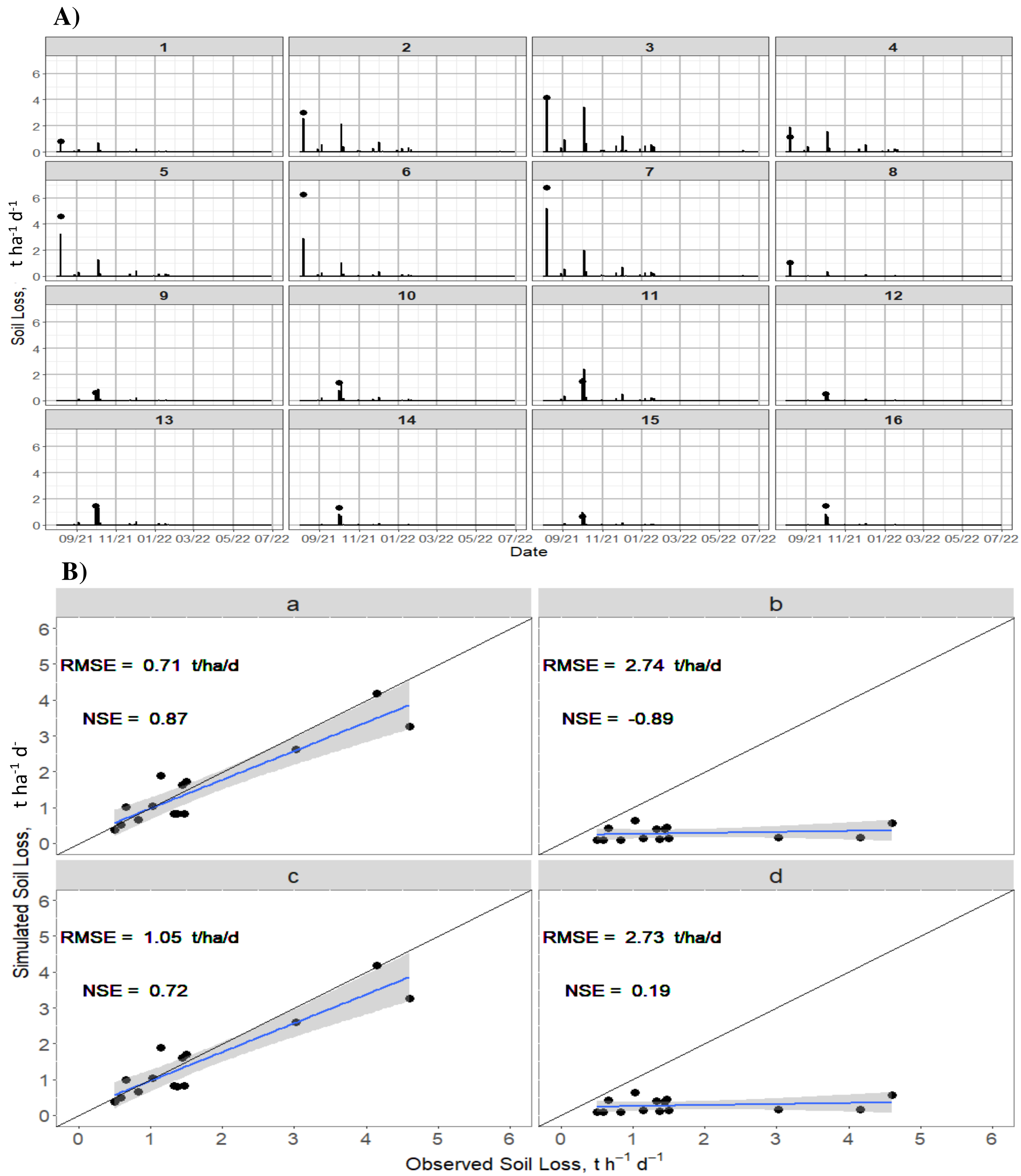


Fig. 4. 13: Freebairn model simulation for sediment prediction; (A) validation of sediment yield during the cropping season 2021-2022 of Rapeseed crop (B) 1:1 line relationship between simulated and observed sediment yield for the validation of the Freebairn erosion model combined with the outputs of calibrated or uncalibrated vegetation and runoff models; (a) Freebairn model combined with calibrated Lintul5 & runoff models, (b) Freebairn model combined with calibrated Lintul5 model only, (c) Freebairn model combined with calibrated runoff model only, (d) Freebairn model combined with uncalibrated Lintul5 and runoff models

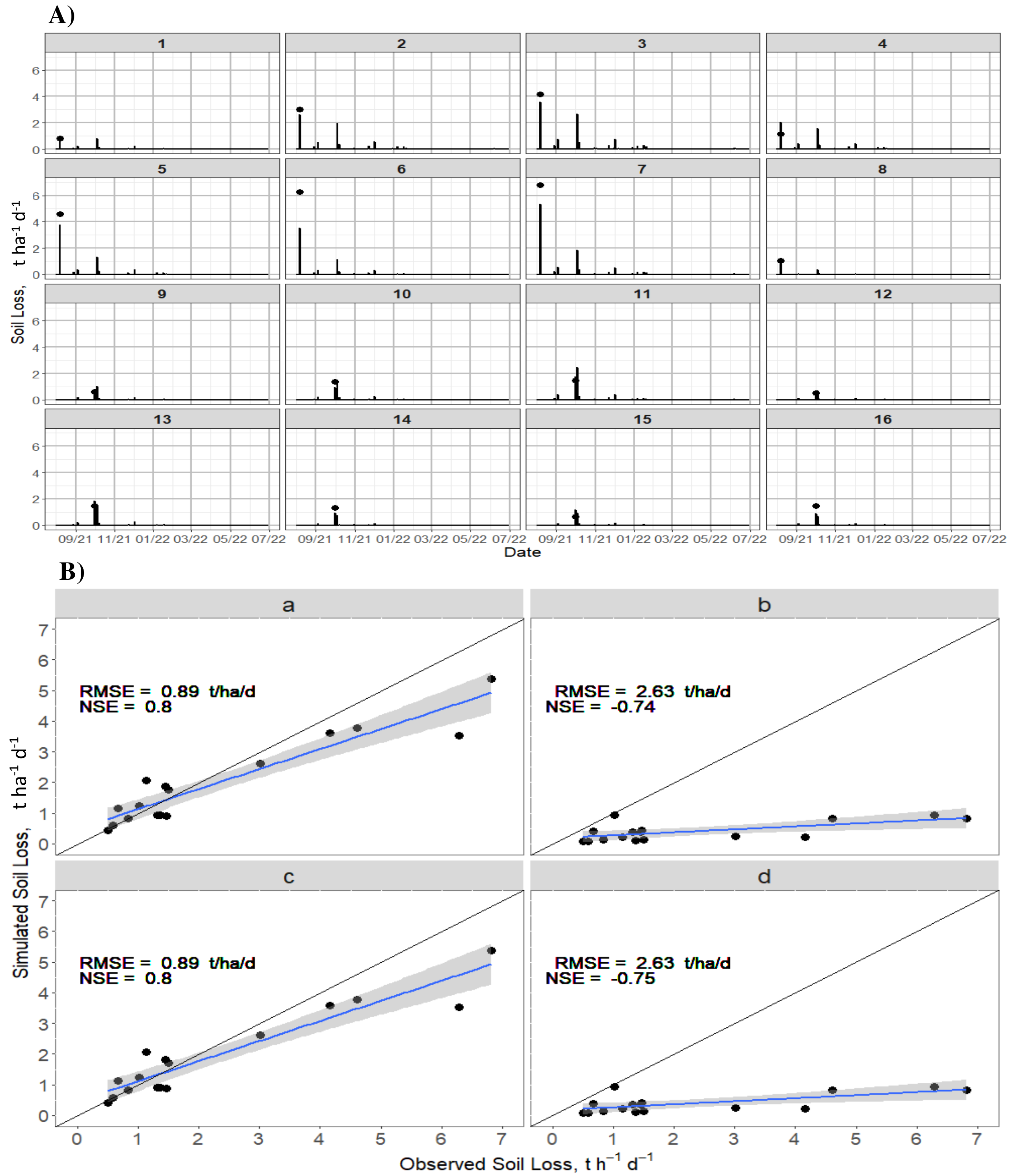


Fig. 4. 14: Rose model simulation for sediment prediction; (A) validation of sediment yield during the cropping season 2021-2022 of Rapeseed crop (Black points represent observations) (B) 1:1 line relationship between simulated and observed sediment yield for the validation of the Rose erosion model combined with the outputs of calibrated or uncalibrated vegetation and runoff models; (a) Rose model combined with calibrated Lintul5 & runoff models, (b) Rose model combined with calibrated Lintul5 model only, (c) Rose model combined with calibrated runoff model only, (d) Rose model combined with uncalibrated Lintul5 and runoff models

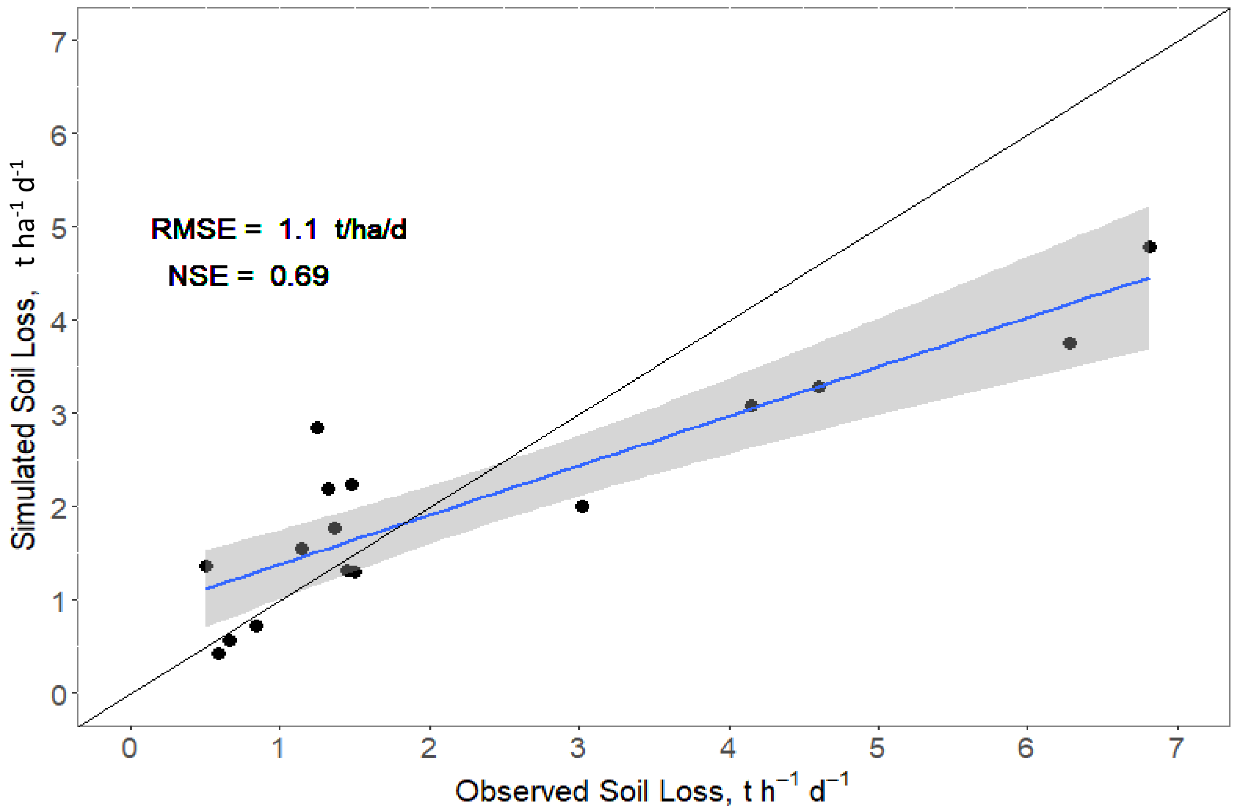


Fig. 4. 15: Validation of local model for sediment prediction

4. Conclusion

This study aimed to provide insight into the uncertainties that are involved in the simulation of sub-field scale run-off and soil erosion processes due to the model structure. Therefore, three different sediment yield models (local statistical model, dynamic Freebairn, and Rose model) were combined with the outputs of calibrated and uncalibrated runoff and vegetation models as well as vegetation cover (LAI) observations. The simulations of water erosion with dynamic Freebairn and Rose models were influenced by the performance of runoff and crop growth models. However, a pronounced difference was found between modeled and measured soil erosion when these predictions were made with an uncalibrated runoff model. Hence, our results highlighted that large uncertainties in soil erosion modeling were associated with improper performance of the runoff model.

The most sensitive parameters affecting sediment yield simulation in the Freebairn model were field topography, soil erodibility factor, and runoff. The most sensitive parameter affecting sediment yield in the Rose model was the efficiency of entrainment λ. Entrainment by the surface flow became the dominant mechanism contributing to sediment transport when vegetation cover is small and it drastically influences the sediment yield. Our results demonstrated that these parameters are the key site factors affecting the performances of predicting soil loss by the Freebairn and Rose models in heterogeneous field conditions.

The dynamic models and local statistical model were successfully applied in the study area, the obtained outcomes were relatively close to the observations. The findings give considerable confidence in the model structure. Therefore, it can be concluded that both Freebairn and Rose models can be used as tools to predict sediment yield within the SIMPLACE framework. However, it should be noted that selected models were tested with prevailing local environmental and field conditions in the study area, which implies that these conclusions only apply to the field with characteristics similar to the study area. The preferred criteria to select these models were identified through the combined consideration of model structure, data availability, and the SIMPLACE framework. Further improvements of soil erosion models should focus on enhancing the data quality for model applications and improving the representation of these models in terms of their scales and objectives.

Chapter 5

General Discussion

1. General Discussion and Conclusions

1.1. Challenges in field scale erosion process modeling under heterogeneous field conditions

Results of chapter 2 showed that soil erosion models are subjected to certain limitations sourced from their development objectives (Q1-Table 1). These objectives most often are derived from the site-specific environmental conditions and scale of the erosion process. However, individual hydro-geomorphological processes and vegetation cover impact differently on the soil erosion process across various scales which influences the model calibration and model performance. Calibration of field-scale models based on data from fields that are characterized by a high spatial heterogeneity of topography and soil types is more accurate than using averaged data from larger catchment areas. Hence, calibration of the field scale model requires a large input data set with multiple factors which may spatially vary drastically even in a single field.

Field conditions predominantly influence the model input data requirement and data quality. Thus, controlling the level of complexity in the model calibration process. This has a remarkable influence on the simulation of soil erosion, runoff transportation capacity, and sediment deposition. Our results depicted that among different field conditions, "slope" is particularly one of the major factors in the erosion process and plays a key role in modeling process. For models using USLE to reflect the effect of slope length on soil erosion, the major problem (Q1-Table 3) is the suitable selection of slope segments in fields with complex topography where slope characteristics may vary drastically at field scale. The other important factor is the soil physical and hydrological properties with spatially heterogeneous nature within a field that define the limitations of field scale models in representing the soil erosion process. For instance, EPIC predicts soil losses from the flows in rill areas only. Whereas EUROSEM, WEPP, and GLEAMS estimate soil losses from rill and inter-rill areas separately (Q1-Table 3).

Furthermore, the accuracy of the simulation of erosion rates depends on the spatial dimension taken into account, i.e. whether processes are simulated at the soil profile scale (1D, point based assuming a field with homogeneous soil and terrain conditions) and/or whether spatially distributed or multi-dimensional method (2D/3D) are applied. A particular shortcoming of most of the existing field scale models is their one-dimensional nature. The quality and accuracy of the calibration of the field scale models in heterogeneous fields should increase with the dimension that is considered

(Q1-Table 6). However, the results of this study revealed that the availability of accurate soil information is a major bottleneck for multi-dimensional models.

1.2. Challenges in field scale erosion process modeling under complex cropping systems

Similar to the impact of heterogeneous field conditions (slope, soil physical, and hydrological properties), the field scale soil erosion process is also greatly affected by the type and the dynamics of the cropping system. Tools are required to predict the impact of diverse cropping systems on the soil erosion process. The results of Q1 showed that there are no modeling techniques yet available to represent the soil erosion process in complex cropping systems such as alley cropping, row and strip intercropping, patch cropping, and agroforestry (Fig. 5.1). Motivated by the previous section (5.1), models were specifically studied to evaluate their capabilities to simulate the erosion process under such cropping systems.

Fig. 5. 1: Agroforestry system at research site

A few soil erosion models coupled with dynamic cropping models investigated the soil loss and surface runoff but they do not explicitly focus on the impact of mixed vegetation cover on soil detachment and generation of surface runoff at the field scale. For instance, Water Nutrient and Light Capture in Agroforestry Systems (WaNuLCAS) potentially is able to simulate processes in agroforestry systems but there is a lack of evidential reports on its capabilities to simulate soil erosion in agroforestry systems. Although some attempts are being made to improve soil erosion models, there is still room to develop tools that consider the representation of soil erosion processes under complex cultivation patterns on the same field.

An important cause of model simulation uncertainties in complex cropping systems is the increasing importance to estimate overland flows under varying spatial arrangements and temporal dynamics of different canopies on an agricultural field. Modeling capabilities should be improved and tested with respect to the soil erosion process in strip and patch cropping systems as well as agroforestry systems. Existing agroforestry models must be improved to incorporate erosion processes in fields with high spatial heterogeneity with respect to soil properties, slope inclination, and length, preferably considering three dimensions. Such new developments might also support upscaling of soil erosion processes to larger spatial scales (watershed to basin scale).

1.3. Challenges in measuring soil erosion considering the multiple drivers involved: Understanding the fine-scale spatio-temporal dynamics of soil erosion processes

The results of chapter 3 reveal that spatial heterogeneity of soil physical characteristics, topography, and temporal variations in soil cover has a considerable impact on the soil erosion process (Q2-Fig. 4) in the study area. A key challenge in soil erosion studies is understanding the connectivity of landscape characteristics and their interactions. In order to better understand soil erosion and soil movement in agricultural systems, research needs to be conducted at the correct temporal and spatial scale at the farm field with intensive data of field conditions. This research was conducted in a field which has been selected to represent a typical situation in the landscape formed by the last glaciation in North East Germany. This region is intensively used as cropland and is characterized by soils formed from the glacial till of the last glacial period and later modified by fluvial and erosive processes. Thus, it created an enormous small-scale heterogeneity in the landscape and in vulnerability to the soil erosion process.

In concordance with the results, different scenarios tested showed that soil erosion and runoff responded differently under different combinations of factors and their complex interactions within a single field of 6 hectares (Chapter 3-Table 3.1). Thus, the combination of factors and their interactions were identified causing potential soil loss and runoff under given field conditions (Chapter 3-Table 3.4). Rainfall intensity and slope steepness had a remarkable influence on the amount of sediment yield and volume of runoff. Based on the results, it was suggested that the highest sediment yield should be obtained with the factor levels combination of 4, 2, 4, 4, 1 of Silt and organic matter, vegetation cover, slope steepness, rainfall intensity, and depth to loamy layer respectively. On the other hand, the lowest sediment yield should be obtained with the factor levels combination of 1, 4, 1, 1, 2 of Silt and organic matter, vegetation cover, slope steepness, rainfall intensity, and depth to loamy layer respectively. The highest rainfall intensity (>4 mm min^{-1}) led to the highest volumes of runoff, followed by the factor vegetation cover (maximum values at Level 4). Runoff was mostly influenced by rainfall intensity followed by vegetation cover, and slope. The stronger impact of vegetation cover compared with the slope can be explained by the stronger variability of vegetation cover at different soil management stages during the experimental period in the study area. Moreover, earlier studies showed that surface runoff depth is sensitive to the plot size and type of vegetation. From our results, it is also depicted that erosion studies are limited by their size, i.e., constrained to experimental research plots, it can be difficult to interpret the results in both space and time to represent landscape connectivity and small-scale process domains. The results point out the need for further research to quantify the influence of the plot size on sediment yield and surface runoff.

Although the previous studies have already considered the simultaneous influence of a few factors on the soil erosion process (Barthès and Roose, 2002; Ouyang et al., 2018; Panagos and Katsoyiannis, 2019; Ramezanpour et al., 2010), the work described in chapter 3 is the unique approach of fractional factorial design to investigate the combined impact of multiple factors and their complex interactions on soil erosion process by selecting an optimized number of experiments. The applied workflow allowed for efficiently predicting soil erosion and identifying areas susceptible to soil loss at a high spatial resolution (Chapter 3-Table 3.4). Based on the findings, statistical regression model were developed for runoff volume and sediment yield and applied to the whole study field. When statistical model are up-scaled to the whole field, the statistical model performed well for the lower rainfall intensity (< 2.7 mm min^{-1}) but its performance declined when rainfall intensity further increased (> 4 mm min^{-1}). The results show that the South West of the study area is subjected to potential soil loss due to erosion, which is in accordance with the on-site field observation and measurements (Chapter 3-Fig. 3.8). However, these studies were specific to local soil conditions and for a given area. The performance of the local model with the validation data set showed the highest uncertainties in simulating sediment yield with an RMSE value of 1.1 t $ha^{-1}d^{-1}$ among erosion models in this study (Chapter 4-Fig. 4.15). This is because of the specific environmental conditions (soil physical characteristics, topography, and vegetation cover) during the development of the local statistical model. Further, this model might facilitate the application of erosion control measures within fields with high spatial heterogeneity if improved with different field conditions at different sites.

An improved understanding of complex interactions among multiple factors influencing the soil erosion process is an important area of research for future soil erosion studies, since this understanding of connectivity between small scale field conditions in the agricultural landscape is as important as understanding absolute sediment yield. Since plot-based studies have complexities in upscaling the predictive modeling techniques at complex agricultural landscapes, it is important to quantify the collected data quality and adequacy from plot-scale studies to better understand soil movement at large scale. From the results of our study it can also be recommended, that for regions where soil characteristics and topography are unevenly distributed, methods such as Taguchi fractional factorial design might be suitable and sufficient to represent the factors that influence the soil erosion process at the field scale. Such design is limited by the number of experimental arrays, application of these designs on the agricultural fields with heterogeneous field conditions, and lack of explicit randomization of that limit its utility, but many other competing fractional factorial designs have some of same limitations and significantly more complex (montgomery, 1990). However, this approach allows for an accurate representation of the soil erosion process in the context of agricultural systems.

1.4. An overview of the workflow of soil erosion modeling

The parameters of plot/field scale soil erosion models affect the soil erosion process simulations and therefore typically are valid for the scale and field conditions for which they were determined. Due to spatial and temporal variations in factors influencing the soil erosion process (i.e., slope, soil characteristics, vegetation cover, and rainfall intensity), it is crucial for the calibration of models used in plot scale applications that model parameters reflect the spatial variability of such soil erosion influencing factors. Uncertainties in soil erosion simulations due to input parameters have been studied in for many models and environmental conditions (Brazier et al., 2000). However, the majority of studies undertaken in the context of plot scale soil erosion simulation have not investigated uncertainties caused by the approaches to couple processes, such as soil water fluxes, crop growth, and soil erosion. In this dissertation, chapter 4 (Q3) deals with the soil erosion estimates from three different sediment yield models (local statistical model, dynamic Freebairn, and Rose model) combined with a soil water balance, a runoff and a crop model to identify the uncertainties involved in the simulation of sub-field scale runoff and soil erosion processes due to parameter estimation and model structure. The study did not pursue simulating the long term soil erosion process but to identify sources of uncertainties in simulation results when soil erosion models coupled with crop growth and runoff models within the SIMPLACE modeling platform.

In this dissertation, a workflow was established to couple the Lintul5 crop model, with the SlimWater soil water balance model including the CN runoff model and with three different soil erosion models as a solution of within the SIMPLACE platform. The objective of this solution was to simulate the soil loss on the agricultural field, where plot-scale erosion processes where monitored in chapter 3. This novel workflow allowed us to directly quantify the seasonal distribution of soil erosion processes across plots with different soil conditions and topography. In conjunction with our plot-scale erosion measurements, we used a LiDAR digital surface model of the farm field as topographic inputs, SlimWat model to give us further insights into the soil hydrology.

The results from model calibration based on plot-scale measurements showcased that water erosion estimations with Freebairn and Rose models were influenced by the accuracy of runoff and crop growth models in simulating runoff and vegetation cover respectively. However, a pronounced difference between modeled and measured soil erosion was observed when these predictions were made with the uncalibrated runoff model. Hence, our results highlighted that large uncertainties in soil erosion simulations were associated with the runoff model. Clearly, our results emphasize the need to consider uncertainty due to calibration as integrated part of the general reporting of uncertainty (Keating et al., 2003b). It should thus also be part of a common protocol to assess uncertainty in soil erosion modeling applications.

The accurate predictions of the Freebairn and Rose models, when validated with our plot-scale measurements, allowed us to simulate sub-annual crop growth and soil water dynamics across our study site which provided insights into key parameters influencing the temporal distribution of erosion processes. Most notably, the Rose model had a limitation in sediment yield prediction and showed slightly higher RMSE (0.89 t ha^{-1} d^{-1}) and NSE (0.8) compared to the Freebairn model when coupled with the same soil water balance and crop model approaches. On the other hand, the performance of the local statistical model, when compared against the validation data set, showed the highest uncertainties in simulating sediment yield among all erosion models in this study with an RMSE value of 1.1 t $ha^{-1}d^{-1}$. These uncertainties may reflect the limitations of applying statistical models under conditions which do not correspond to the prevailing specific environmental conditions under which they were developed (soil physical characteristics, topography, and vegetation cover). The Freebairn and Rose models were specifically selected to integrate with crop growth and soil water balance models to simulate short/long-term soil loss estimates by the process-based representation of climate, vegetation dynamics and hydrology.

The newly developed SIMPLACE<Lintul5, SlimWater, Erosion model> workflow can be used to provide time series of detailed spatially distributed simulations of soil erosion. However, the workflow was tested under the prevailing local environmental and field conditions in the study area, which implies in the first place, the workflow should only be applied to areas with similar climate, soil and terrain characteristics. This may provide the motivation for future researchers to improve the modeling framework for a better representation of the soil erosion process in the context of the spatial and temporal distribution of model input data and its quality. Furthermore, there is room to assimilate UAV-based data, for instance, UAV-based estimates of crop height, LAI or above-ground dry biomass to be implement into this workflow for soil erosion studies in agricultural systems. These additional datasets can be explored as additional source of information for reducing the uncertainties in the model simulations when extrapolated to larger regions or for model validation in other landscape settings.

1.5. Conclusion

After having a systematic evaluation of the impact of spatial and temporal heterogeneous field conditions on the soil erosion process, and assessment of sources of uncertainties in soil erosion model simulation results, the following general conclusions can be drawn:

1. In agricultural systems with complex spatial arrangements of crops, where vegetation dynamics and spatial configuration plays a crucial role for the soil erosion process, current modeling approaches do not necessarily represent their effect in complex agriculture systems on soil loss estimations.

2. A range of experimental settings with different rainfall intensities, spatial variations of soil characteristics, vegetation cover, and slope inclination produced a wide range of sediment yields and volume of runoff. Highest sediment yield was found with the factor combination of rainfall intensity (> 4 mm min^{-1}) and slope steepness (5%) in bare land field with SiltOM content of 16%. and the lowest sediment yield was observed with the factor combination of rainfall intensity (> 2.5 mm min^{-1}) and slope steepness (<1 %) with vegetation cover > 15%
3. Since a combination of multiple factors and their interactions have complications in representing the soil erosion process, the developed workflow in chapter 4, allows for efficiently predicting soil erosion and identifying areas susceptible to soil loss at a high spatial resolution of field conditions.
4. The uncertainties, resulting from the model structure, in the performance of dynamic soil erosion models are very important to consider when applied at plot scale as have been shown in this study (Chapter 4).
5. The Freebairn and Rose models can be used as tools to predict sediment yield within the SIMPLACE framework with prevailing local environmental and field conditions in the study area. However, the performance of runoff component plays a key role in accurate sediment yield predictions. Further improvements in meaningful input data to up-scale the model applications need to be given attention in the future.

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Appendix

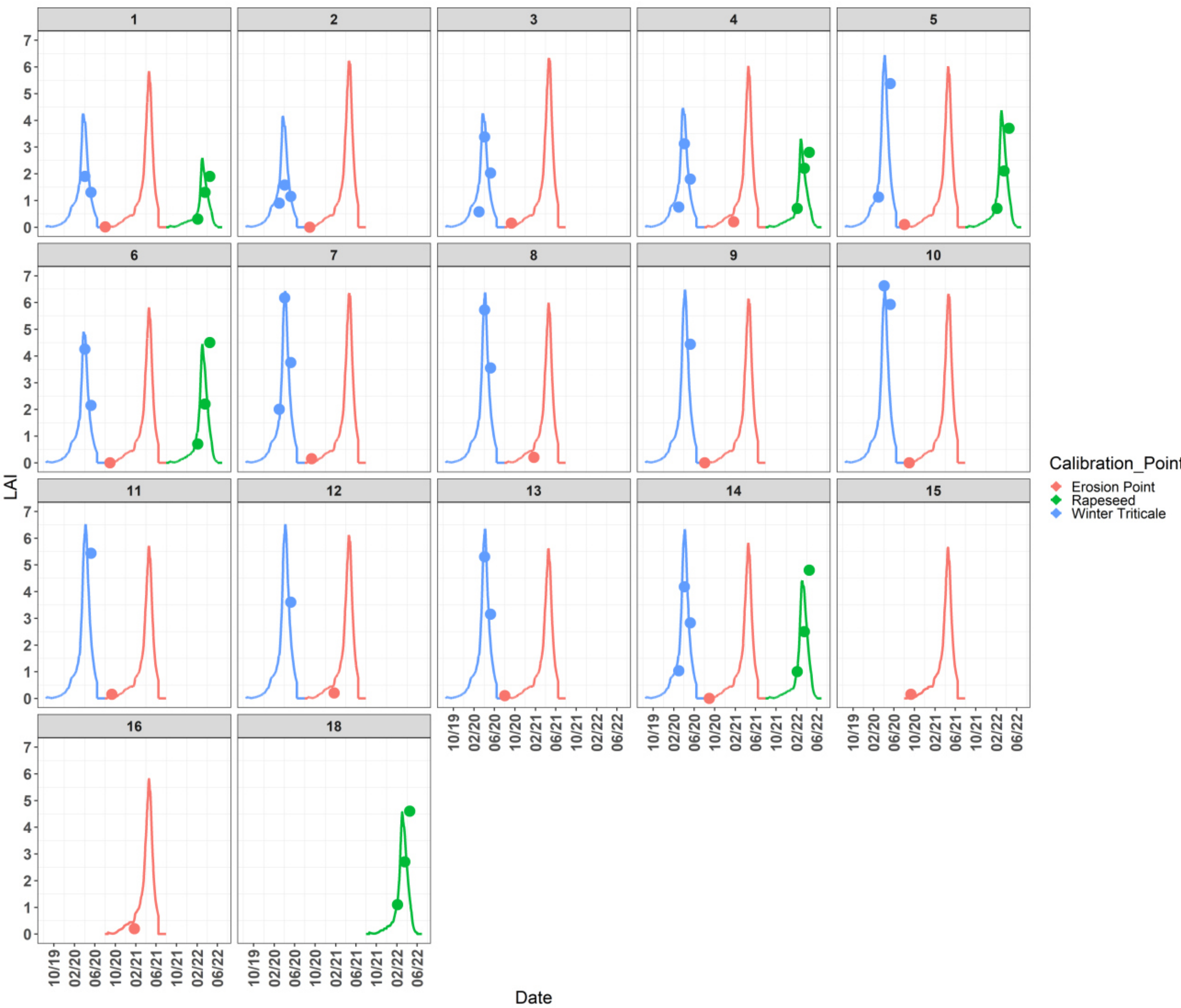

Fig. 1. Modelled (Line) and observed (Dots) leaf area index for the calibration

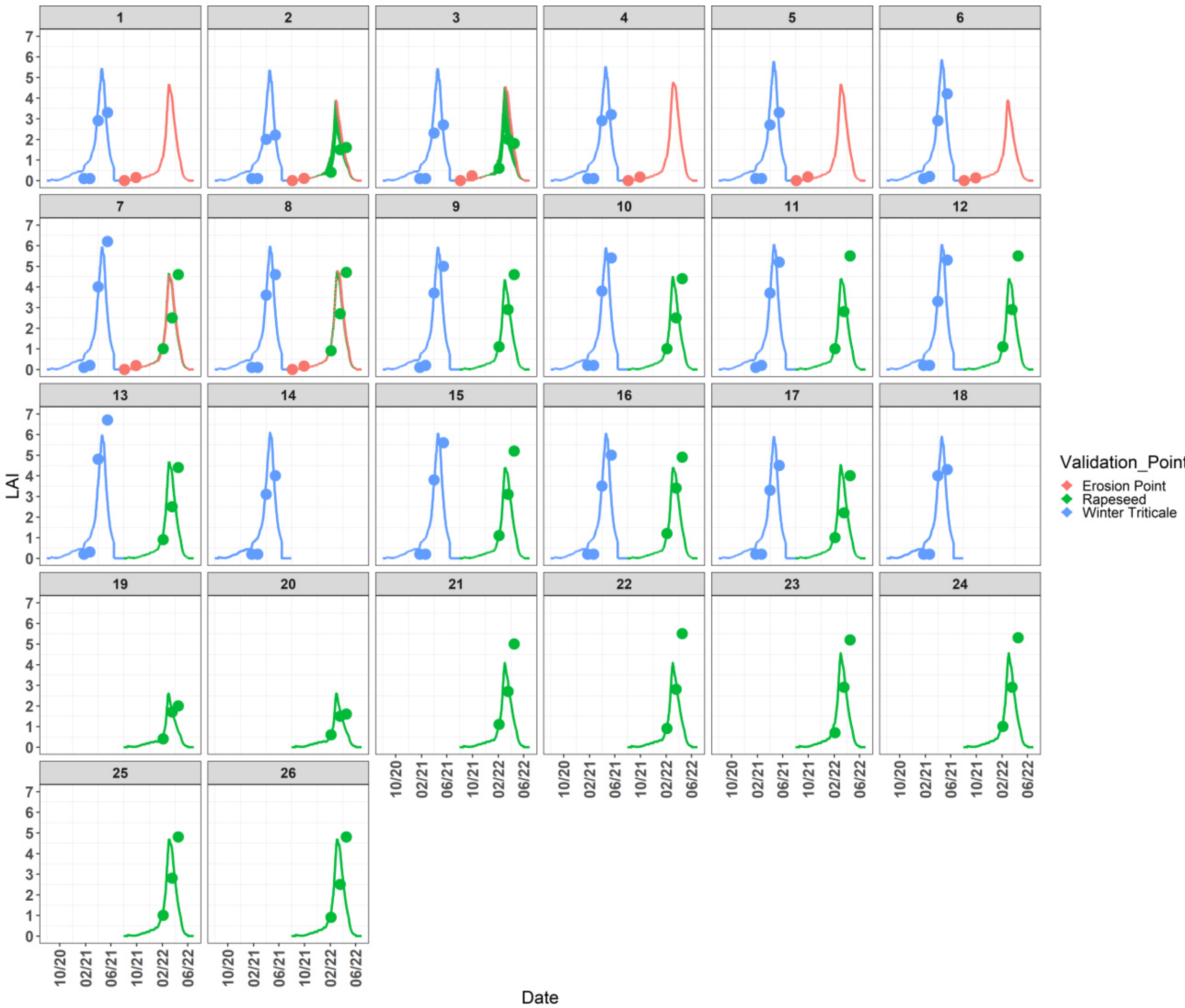

Fig. 2. Modelled (Line) and observed (Dots) leaf area index for the validation

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