An environmental assessment of gully erosion susceptibility in Chambal ravines of India: Geospatial and machine learning based approach

インド・チャンバル渓谷におけるガリー侵食の起こりやすさの環境評価：地理空間情報および機械学習によるアプローチ

Ph.D. Thesis Submitted by

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by

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Declaration

I hereby declare that the work presented in this thesis has not been submitted for any other degree or professional qualification and that it is the result of my own independent work.

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Abstract

The study of ravine and gully erosion is one of the significant aspects of environmental science. Ravine and gully erosion is the most hazardous form of land degradation caused by the water-induced soil erosion process. It may impact ecosystem function, soil productivity, water quality, crop failure, and the quality of human life surrounding it, well known as Badland. Especially in India, as an Agricultural country and high population country, Badland is the biggest threat to food security and economic development. Hence, the government and several national and international organizations are trying to manage and mitigate this problem through the ravine reclamation program. One of the most crucial parts of ravine reclamation is gully erosion assessment, erosion susceptibility, and the accurate estimation of its magnitude. Also, gully erosion assessment gained huge scientific and social interest owing to its severe consequences. Geospatial data with machine learning algorithms has been accepted as the most efficient and effective way to monitor ravine and gully erosion.

In this study, the lower Chambal valley of the Indian ravine has been considered to study gully erosion susceptibility using geospatial data and machine learning methods. Chapter 1 focuses on the Introduction and background information on ravine and gully erosion, the motivation of this study, the goal and objective, and the content of this thesis. While Chapter 2 describes the study area i.e., the Bhind region in central India. This chapter gives details about the location of the area, geomorphology, geology, climate, flora and fauna, environmental condition, and socio-economic condition. It also includes information about ravines reclamation projects for Chambal ravines in India.

Chapter 3 covers the literature review part, which synthesized and summarized the comprehensive review of methodologies applied for the Ravines and Gully erosion assessment. It also discusses the decadal change in satellite sensors and the advancement of methods and their pros and cons. The literature review was used to select the study area, data, and methodology to pursue the research.

Chapter 4 focuses on gully erosion assessment through gully erosion volume changes analysis and erosion susceptibilities of Badland in Chambal, India using the multi-temporal TerraSAR-X DEM (TanDEM-X) dataset acquired for 2012 and 2017. This chapter addresses the quantification of gully erosion volume change with a framework to predict the gully erosion volumes and soil erosion rate in the area of interest. It also evaluates the factors that control gully erosion and maps the gully erosion susceptibilities. The result shows that about 40% of the area is highly affected by gully erosion, with the maximum gullying process in north-central and lowest in the west-south location of the testing area. Plus, the rate of gully erosion that causes volume change in the study area is 283 t ha^{-1} yr^{-1}. The research framework presented in this study can be helpful in the erosion rate estimation of the Chambal ravine and other ravenous areas and can be utilized effectively in ravine reclamation projects.

Chapter 5 of the thesis focuses on the effect of DEM (Digital Elevation Model) characteristics on machine learning in gully erosion susceptibility. It is toward developing a concept about the selection of the DEM and the suitable DEM resolution in gully erosion assessment. The study in this chapter reveals, the unexplored effect of the DEM resolution from different sources on the accuracy of gully erosion susceptibility mapping (GESM) using the Random Forest (RF) algorithm. The six different DEMs has been considered for this analysis are TanDEM-X (5m), SRTM (30m), ALOS PALSAR (12.5m), ASTER GDEM (30m), AW3D (30m), MERIT (90m). The 5m TanDEM-X confirmed the highest accuracy. However, the order of accuracy with respect to DEM resolution is TanDEM-X (5m)> AW3D (30m) > SRTM (30m)> ALOS PALSAR (12.5m)> MERIT (90m)> ASTER GDEM (30m). Hence, this evaluation predicted that the finer resolution of DEM data favors attending high accuracy to study GESM but not necessarily because the DEM source, type of sensors, and other satellite features are also influential in gaining good quality topographic data.

Chapter 6 is the conclusion and the key finding of this study. This chapter includes the contribution of the study in scientific, environmental, and social aspects. It also includes the significance, novelty, and future recommendations of this study.

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I am dedicating my work to the **almighty God, Mother Nature,** and this beautiful world.

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Chapter 1: Introduction

1.1 Research Background

Land is one of the basic resources to sustain life on earth. It provides vital life-supporting elements for humans, plants, and other species and supports the planet's major biodiversity and ecosystem (Keesstra et al., 2018; Razavi-Termeh et al., 2020). Along with hosting several ecosystems, land contributes to the soil ecosystem, one of the most crucial parts which provide the house for microbes and essential nutrition for plants (Bot & Benites, 2005). However, It is always vulnerable to erosion and degradation by natural or anthropogenic activities. Soil erosion by the dynamics of water is often the biggest issue in human society, and it induces severe land degradation problems. Earth is already facing several environmental problems and declining natural resources; land degradation is also one of the most concerning issues on this list. Besides all the natural resource depletion in the world, land degradation is one of the most devastating natural hazards and has always been an issue on the international agenda. In the context of land degradation, ravines and Gully erosion is the most severe form, and is a threat to the environment, human and whole ecosystem of that area.

Approximately 10 million hectares of the world’s cultivated land are the victim of land degradation (Derose et al., 1998). Land with the existence of gully erosion or ravine formation is highly vulnerable to degradation and desertification. Ravines and gully erosion have destroyed the land and affected the environment worldwide. Some countries like Iran, South Africa, New Zealand, India, China, Italy, Belgium, etc. are the most considerable victims of land erosion and degradation. Hence, the Sustainable Development Goal (SDG 15) advocates “Life on Land”, the ambition is ‘By 2030, combat desertification, restore degraded land and soil, including land affected by desertification, drought, and floods, and strive to achieve a land degradation–neutral world’ (UN, 2019). Land Degradation Neutrality program has been defined and adopted in the 2030 agenda for Sustainable Development (UNCCD, 2012). This SDG cannot be completely achieved without taking care of the land degradation problem. Assessment of ravine and gully erosion is one of the significant strands of land degradation hazards. For this purpose, gully erosion hazard risk estimation and gully erosion susceptibility mapping are particularly important and are the first step toward this process. With the help of available data from different sources, such as remote sensing data, published evidence or information on land use and a deeper understanding of the nature of land degradation in the region and advanced technology like machine learning would certainly help in gully erosion assessment and in minimizing land degradation of the region.

The present study has focused on the environmental assessment of gully erosion susceptibility by using remote sensing and machine learning techniques. Although the study is completely based on the availability of geospatial data and not on geomorphological surveying, it is an attempt to perform the gully erosion assessment, which can be done with the help of advanced technology of GIS and machine learning, in the absence of geological surveying opportunity.

Recently several published papers have applied various machine learning models for gully erosion susceptibility mapping. Machine learning techniques have already contributed significantly to landslide susceptibility. With the emergence of machine learning techniques, some of the classifiers such as random forest (RF), boosted regression trees (BRT), artificial neural network (ANN), and support vector machine (SVM), have contributed significantly to the field of susceptibility mapping of landslide (Catani et al., 2013; Gorsevski et al., 2016), debris flow (Yuan et al., 2006) and ground subsidence (Oh & Lee, 2011). In recent years various machine learning models, such as decision tree (DT), SVM, and ANN have been employed to predict gully initiation at the catchment scale, and comparison of their results with the analytic hierarchy process (AHP) and topographic threshold (TT) methods (Svoray et al., 2012). Lately, Kuhnert et al., 2010 applied the RF model to predict gully density and the gully erosion rate through a suite of environmental predictors and to estimate the prediction uncertainty. Bringing out a valid and accurate prediction of gullies is still challenging due to the complex nature of gully erosion, such as the soil condition, lithology, topography, hydrology, and human activities. Despite the many efforts that have been made in gully erosion susceptibility and hazard modeling, there is still a dispute over which model or technique is the best for the identification of gully-prone areas. Rahmati et al., (2017a) evaluated the performance of seven advanced machine learning models for predicting the spatial occurrence of gully erosion. This study found that in terms of accuracy, the RF, RBF-SVM, BRT, and P-SVM models performed excellently both in the degree of fitting and in predictive performance and stated that these models could be used in other gully erosion studies, as they are capable of rapidly producing accurate and robust gully erosion susceptibility. Primarily, it was found that the performance of RF (random forest) for modeling gully erosion occurrence is more stable. The random forest model for gully erosion susceptibility assessment has been accepted as the most reliable and accurate and hence it has been applied in several studies (Gayen et al., 2020a; Pourghasemi et al., 2017; Saha et al., 2020).

1.2 Concept of Ravine and Gully Erosion

There are many types of soil erosion, but earth scientists are overly concerned with accelerated erosion, where the rate of erosion increases due to human intervention, such as ravine or gully erosion. The gully erosion process is defined as a deep channel induced by a concentrated flow of water, which removes the upper parent material and leave the land unfertile (Fig. 1-1). The size of the gully is larger than the rill and it cannot be ceased by the normal tillage process (G. Kumar et al., 2020; Poesen et al., 2003). It is the continuous depression on the land surface created by the soil displacement by the water channels. Ravine is the final stage of the gully erosion process, characterized by loosely bonded soft sedimentation comprised of the complex network of several of gullies that run almost parallel to each other. Ravine formation and gully erosion process is a natural phenomenon, initiated by the flow of river channels and accelerated by uncertain and short-duration high rainfall, loosely bound alluvial soils, undulating landscape, etc. it is highly controlled by variables related to climate, topography, vegetation, geological structure, character of streams and land use practices (P. Kumar, 2007).

In addition, gully erosion is also highly influenced by anthropogenic activities like Improper land use, subsidence agricultural practices, overgrazing, clearing vegetation, deforestation, etc. (Ionita et al., 2015; Pani & Carling, 2013). The formation of rugged topography in the form of Badland has been posing a severe problem to the environment, ecosystem, agriculture, and irrigation planning. This type of area is a highly unproductive and unprotected ecosystem. Land utilization of ravines is retarded in any development activity, and thus named Badland in many countries. Ravines and gully erosion restrict land use, which highly affects the livelihood of people living in these areas. The socio-economic condition of the population residing in the ravine is very low and mostly under the poverty line (Pani, 2018, 2020b). They are mainly dependent on agriculture for their livelihood, which is difficult because of erosion caused by soil infertility. Apart from this, it also causes a range of environmental hazards, such as desertification, flooding, and sediment deposition in reservoirs, reduces soil fertility, and imposes huge economic loss (Arabameri, Rezaei, et al., 2018; Valentin et al., 2005; X. Zhang et al., 2018).

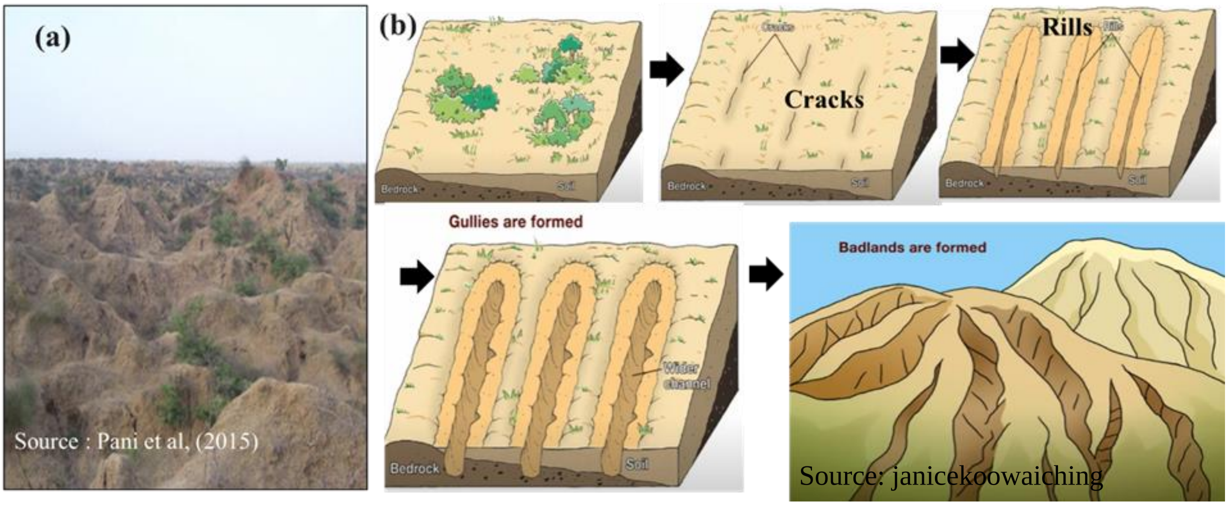


Figure 1-1: Formation of ravine and gully erosion process.

1.3 Ravine and Gully erosion scenario in India

In India, as an agricultural country, gully erosion hazard attends huge economic, environmental, and social importance. Badland of India is one of the most extensive in all over the world, especially the Chambal ravines is biggest and extreme most. In 1976 first authentic and reliable assessment of ravine lands was done in India by the National Commission on Agriculture (NAC), which reported 3.67 million ha of the ravine in India (G. Kumar et al., 2020). The spatial extent of gullies and ravines in India occurs along with some of the major river systems in many states, but the largest is the Yamuna Chambal ravine zone, one of the most extensive Badlands in the world. The Chambal ravines bordered the Chambal River in a 10-km-wide belt and extended southwards from the Yamuna junction to 480 km up to the town of Kota in Rajasthan in the north-west region of India. Ravines also affect basins of several Chambal tributaries, for example, Mej, Morel, Kalisindh, etc. In Gujarat state, the ravine belt is spread over the southern bank of the Tapti, banks of the Narmada, Watrak, Sabarmati, and Mahi basins. Besides these river basins, ravines are also found in the Nort-Eastern side of India like- Jharkhand (Chhota Nagpur), Bihar, and Mahanadi, and upper Sone Valley (G. Kumar et al., 2020) and some parts of West Bengal to north-east India (Dandapat et al., 2020). The state of Uttar Pradesh, Madhya Pradesh, Rajasthan and Gujrat are reported as major ravine states, comprise of 75% of the total ravine area of the country. The area taken into measure in this study is a part of the lower Chambal valley (Chambal ravines), which comes in the state of Madhya Pradesh in central India. It is India's biggest ravine zone and the most extreme one. The area is highly dissected and inaccessible, deep trenches, steep ridges, and low hills are the common feature of the area (figure. 1-2. and 1-3.) (Pani, 2016). This place is characterized by a thick alluvium deposit in the Chambal River and its tributaries.

The current scenario of land degradation and socio-economic condition in the Chambal ravines are mainly attributed to human-induced factors such as agricultural practices and land-use changes (Pani, 2020b). Because of the high loss of topsoil in gully erosion, the area is highly unproductive and unsuitable for agriculture. A large part of the population in the rural area depends on agriculture, which can be done on some patches only where the constant threat of gully erosion hazard is persistent. People in this area are living below the poverty level with very low socio-economic status (Pani, 2020b). From both the ecological and economical perspective, this area highly needs to be redeveloped (Chapter-2, Section-2.9). Several action plans have been started by the state government and national government, including coordination with local and international organizations (Pani, 2016, 2020b; G. P. Verma et al., 2018). Some researchers claim that the ravines can be productively utilized in the economic upliftment of ravine dwellers. The government and local people have initiated the land restoration and ravine reclamation program (Marzolff & Pani, 2018; Pani, 2016, 2018). The main target of ravines reclamation is to mitigate the land degradation process and promote ecological restoration and economic upliftment (Chapter-2, Section-2.10).

Figure 1-2: Image of Chambal Ravine in 2018

Figure 1-3: Image of Chambal Ravine 5-10m deep

1.4 Research Problem, Motivation & Research Focus

Rugged topography, particularly ravines and gullies, continues to be a fundamental problem to the environment and human life. Gully erosion constantly affects agriculture and damages fertile land. The dynamics of gully erosion and its devastations have been attracting the attention of the research community and government for a long time. Especially in India, the huge loss of agricultural land by gully erosion has led to initiate many ravines reclamation programs. The ultimate goal of the ravine reclamation program is to mitigate and restore the land from gully erosion and utilize it for agriculture and other purposes. For reclamation and subsequent usage of Badland, it requires information on its characteristics, spatial distribution, and temporal behaviour, and the immediate task is to check the further growth of ravines. Here, the study area is a highly considered region for the ravine reclamation program but still lacks the information on the magnitude of the problem which is necessary for any reclamation program. There are some attempts have been made earlier by the researchers to map the ravine lands by using available remote sensing data, but all of these studies were based on simple remote sensing tools like- aerial photographs, optical multi-spectral and high-resolution panchromatic satellite data for ravine land mapping purpose (Pani & Mohapatra, 2001). The susceptibility of active gully erosion with its effect on volume change in the area by applying GIS data with advanced technology like machine learning is crucial in the ravine reclamation process for understanding the magnitude of the problem and making a prediction of future scenarios.

The literature review has also revealed that in Chambal Badland of India, the assessment of gully erosion and the geomorphological changes is rarely studied, especially with the use of the machine learning model. No study has tried to estimate the change in volume of the area due to the gully erosion effect. In addition, the importance of the selection of suitable machine learning classifier and DEM (Digital Elevation Model) data for generating efficient methodology and accurate results for gully erosion assessment is still hindered. Important to note that in this study, the volume change of area that occurs due to gully erosion has been estimated for the first time. The study has focused on gully erosion assessment in the Chambal ravines of India between the year 2012 to 2017 and attaining technological enhancement in methodology through understanding the ideal DEM data selection.

1.5 Research Question

- Is there an existence of active gully erosion in the lower Chambal ravine?
- How is the gully erosion affecting the volume of gullied area in the study area?
- What is the rate of gully erosion in the study area?
- How to do the gully erosion assessment with the help of remote sensing and machine learning and without the field surveying opportunity?
- Which Machine learning model is accurate for gully erosion susceptibility mapping?
- How is the DEM data affect the accuracy of gully erosion susceptibility mapping on the machine learning model?
- What can be the ideal DEM data for related research?

1.6 Objective

The overall goal of the study is to monitor the ravines of Chambal Badland, India. The study is aiming to contribute to the ravine reclamation program initiated for Chambal valley development. Focusing on this, there are three main pillars of my study, first one is focusing on ravine erosion assessment, where the study started with the literature review of research that has been done in India and globally to identify what is the research gap, where I found the lack of study is based on gully erosion rate estimation, especially the volume change estimation. Development of a framework for erosion-induced volume change in area is also missing especially by using advanced technology like GIS and machine learning. I started looking into these aspects and set my goal no. 2. Then the study identified the importance of DEM and its resolution parameter in machine learning-based gully erosion assessment, which defines goal no. 3 for the evaluation of various DEM and its resolution effect on Random Forest machine learning.

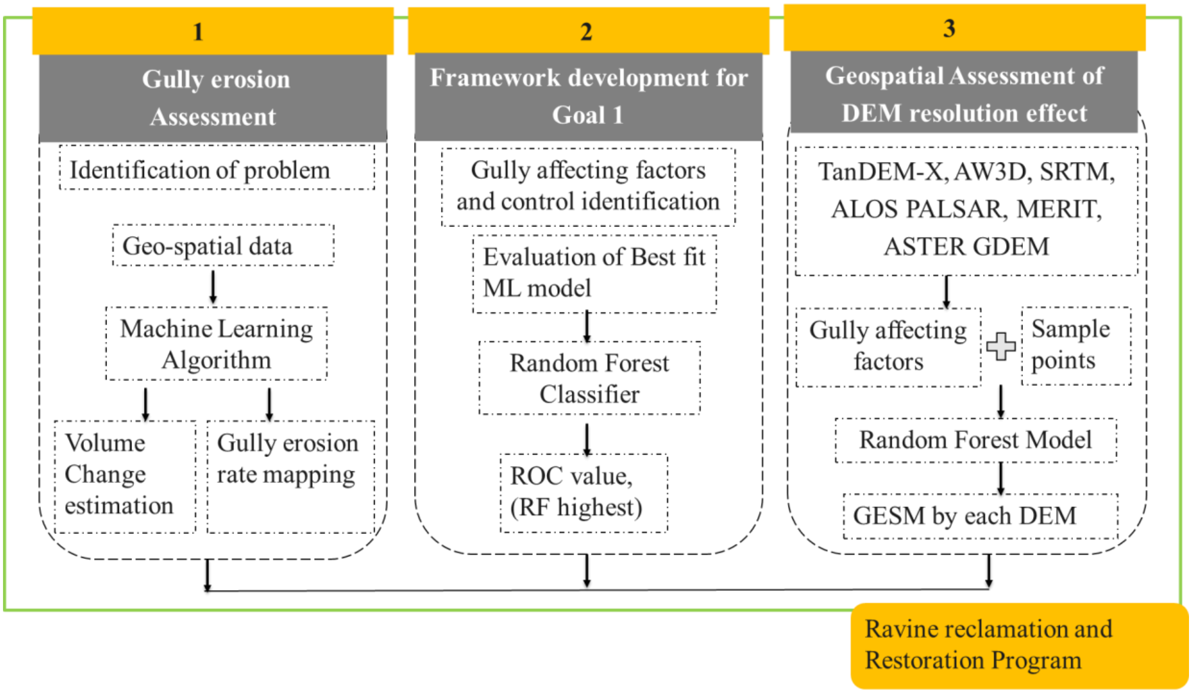


Figure 1-4: Goal of the thesis

Goal 1:

- Identification of problem, research Gap and requirement of study in Chambal ravine.
- To study the susceptibility of active gully erosion in the study area using GIS and machine learning algorithms
- To assess gully erosion by quantifying the erosion-induced volume change in the study area

Goal 2:

- To develop a framework to predict the gully erosion volume and soil erosion rate in the area of interest and its future scope.
- To evaluate the factors that control gully erosion

Goal 3:

- To analyse the effect of DEM from different sources for gully erosion susceptibility mapping.

1.7 Thesis Outline

- **Chapter 1; Introduction:** This chapter is introductory. It gives an outline of the research involved and the research background.
- **Chapter 2; Study Area:** This chapter is an explanation of the study area.
- **Chapter 3; Literature Review:** This chapter is an appraisal of available research in the ravine and gully erosion field of study.
- **Chapter 4; Estimation of gully erosion rate and volume change using TanDEM-X SAR and machine learning models:** This Chapter is based on the study of gully erosion susceptibility and assessment
- **Chapter 5; Evaluating the effect of DEM from different sources in Gully erosion susceptibility mapping:** This chapter is based on the geospatial assessment of DEM from different sources and resolutions in GESM.
- **Chapter 6; Conclusion and Contribution:** This chapter explains the main conclusion of the study with its scientific, social and environmental contribution, significance, and future scope.

Chapter 2: Study Area

2.1 Location of the study area

India has 3.97-million-hectares cultivated land affected by gully erosion, of which 70% is only covered by Chambal Ravine (Upadhyay & Chauhan, 2019). The current study area is the part of Chambal ravine, locally called *Beehad* which means extreme as it is one of the most extreme Badlands of India. It is associated with the Yamuna Chambal ravine zone, bordered by the Yamuna and Chambal River, and extends into many states of India. The area of study falls in the Toposheet nos. 54J/05, 54J/09, 54J/10, 54J/13, 54J/14, and 54N/02 (Geological Survey of India-GSI report, Sep 1990). The area of interest for this study is the part of Bhind district of Madhya Pradesh state, India covers around 4,459 km^2 area. It is situated at 26°69’71’’N to 26°15’17” N latitude and 78°62’08” E to 78°61’94” E longitude (figure 2.1.) (Dwivedi & Ramana, 2003). The most extensive ravine zone covers a large area of Bhind in India and part of the lower Chambal valley. The northern and eastern side of this area is surrounded by Agra, Etawa, and Jhansi districts of Uttar Pradesh and Datiya, Gwalior, and Morena districts of Madhya Pradesh, respectively. This area is fairly connected by the road and railway networks except for the deep ravine area, especially the village is isolated from the rest of area during floods.

The other two locations of Chambal Ravine have also been tested for justification of the selection of the study area. Location-1 is Dholpur, and location-2 is Rajakhera, both of the areas come in the state of Rajasthan and border the neighboring state of Madhya Pradesh. However, the ravines of both of the locations fall on the same gullied track as the Bhind ravines along the Chambal River. Dholpur and Rajakhera are also part of the lower Chambal valley, and near to Bhind region. Dholpur district is situated between 26°12’N to 26°57’ N and 77°14’E to 78°15’E, whereas Rajakhera lies between 26°21’N to 26°53'N and 77°13’E to 78°10' E. Both regions are highly dissected by ravine and gully erosion (NAND, 1966; S. Verma, 2015). Figure 2.1 shows the Chambal Badland on the map of India, together with the location of the study area and two other subsidiary areas in the Chambal ravine belt. The main study area is Bhind, marked with the black dotted box, whereas other subsidiary areas are marked with a yellow star on the map.

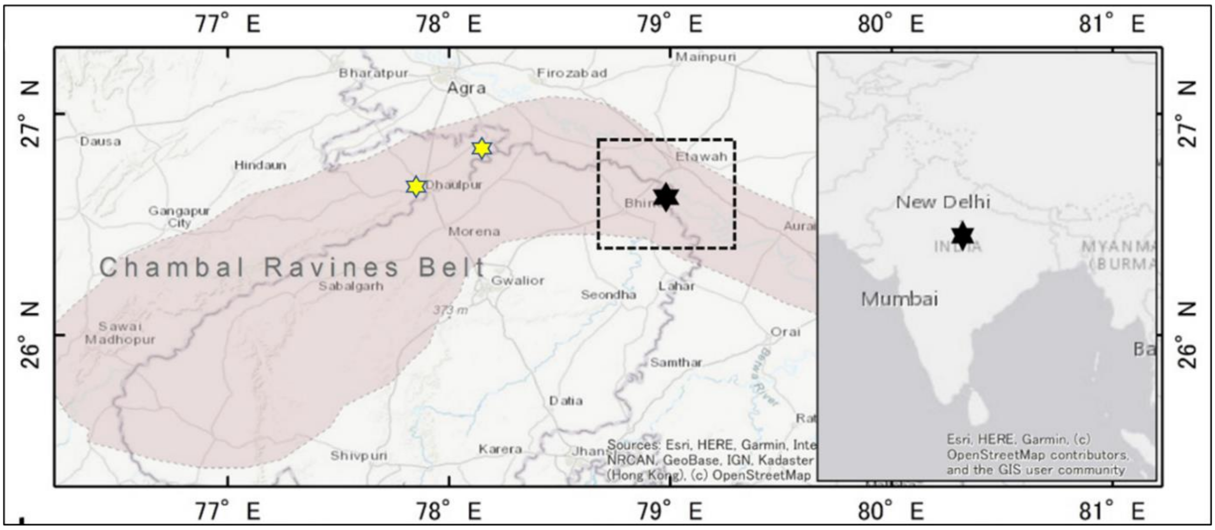


Figure 2-1: Location of Chambal ravine belt, main study area (Bhind) and subsidiary areas (Dholpur & Rajakhera).

2.2 Geomorphology related to the Study Area

Indo-Gangetic plain is one of the huge alluvial plains in the world, created by the formation of the Himalayan Foreland Basin (Gibling et al., 2005). The whole Indo-Gangetic plain can be sub-divided into three geomorphic units i.e., Piedmont Zone (PZ), Central Alluvial Plain (CAP), and Marginal Alluvial Plain (MAP) (Ranga, Mohapatra, et al., 2015; Singh, 1996). The MAP elongated with the Yamuna River and Indian craton, is comprised of the most severe intricate network of gullies, which forms Badland or ravines along the Chambal River, Betwa river, Yamuna, and their tributaries. According to the literature, evidence of neo-tectonic activities has also been recorded in the MAP region, which has been considered to be a notch of rivers and ravines associated with them (Mishra & Vishwakarma, 1999; H. S. Sharma, 1968). The alluvium track of this region has experienced up-warping (bending upward of earth crust) and down-warping (bending downward of earth crust), where Chambal river follows an anti-formal up-warp, and these tilted beds in sediment layers create fractures along the Chambal and Yamuna rivers (Agarwal et al., 2002; Mishra & Vishwakarma, 1999; Ranga, Mohapatra, et al., 2015). This up-warping of the area plus the enormous South-West monsoon in the late Pleistocene-Holocene is also viewed as a potential reason for Badland formation (Tandon et al., 2006).

The 960 km long Chambal River originates from the Vindhyan range and runs through Malwa Plateau, where Vindhyans are covered by the Deccan plateau. The total catchment of the Chambal River has been classified into three parts, Upper Chambal Valley (UCV), Middle

Chambal Valley (MCV), and Lower Chambal Valley (LCV) (H. S. Sharma, 1979). The Upper Chambal valley and Middle Chambal Valley mainly consist of rocky topography, whereas the lower Chambal valley is of alluvium deposits by the Chambal River. The flow of the Chambal River in Lower Chambal valley is controlled by Great Boundary Fault (GBF) and Chambal Jamnagar Lineament (CJL). A huge part of this river flows parallel to the GBF and CJL in the lower Chambal Valley. GBF extends for more than 400 km and runs along the Vindhyan basin boundary and CJL is a 900 km long set of fracture systems and parallel faults. Foregoing active floodplains (now inactive) in LCV (Lower Chambal Valley) and narrow valleys have been inscribed by Badland; in these inactive flood plains, the palaeo-channels have been observed, especially in the lower reaches of Chambal River, which are used in agriculture recently (Figure- 2.2). The active flood plain in this area is limited to the narrow-incised valley along with point bars on the incurved side of the meandering curve (Ranga, Mohapatra, et al., 2015). These active plains are formed by the meander cut-off and side-ward river shifting. There are sharp scarps which are the borderline between the ravine and adjoining inactive flood plains, but these boundaries become amorphous in some areas because of labeling activities on these scarps for some temporary land-use; observed by Marzolff & Pani, 2018; Pani, 2020b; Ranga, Van Rompaey, et al., 2015. Figure 2-2 presents the geomorphological map of a bigger part of Chambal Badland, including the areas considered in this study. Area (a) in the map is the main study area that comes under the Bhind region selected for the current research and (b) in the map is one of the areas tested and compared with the main study area for the justification of selection and falls under Rajkhera region. The other area tested for selection couldn't cover in this map because of data availability. However, all these three regions are part of the lower Chambal valley or Chambal ravines. The map shows a total of 47 geomorphological features; however, the study area is specifically the gullied track, meander, older alluvial plain, active flood plain, older flood plain, river, and some of the point bars along them.

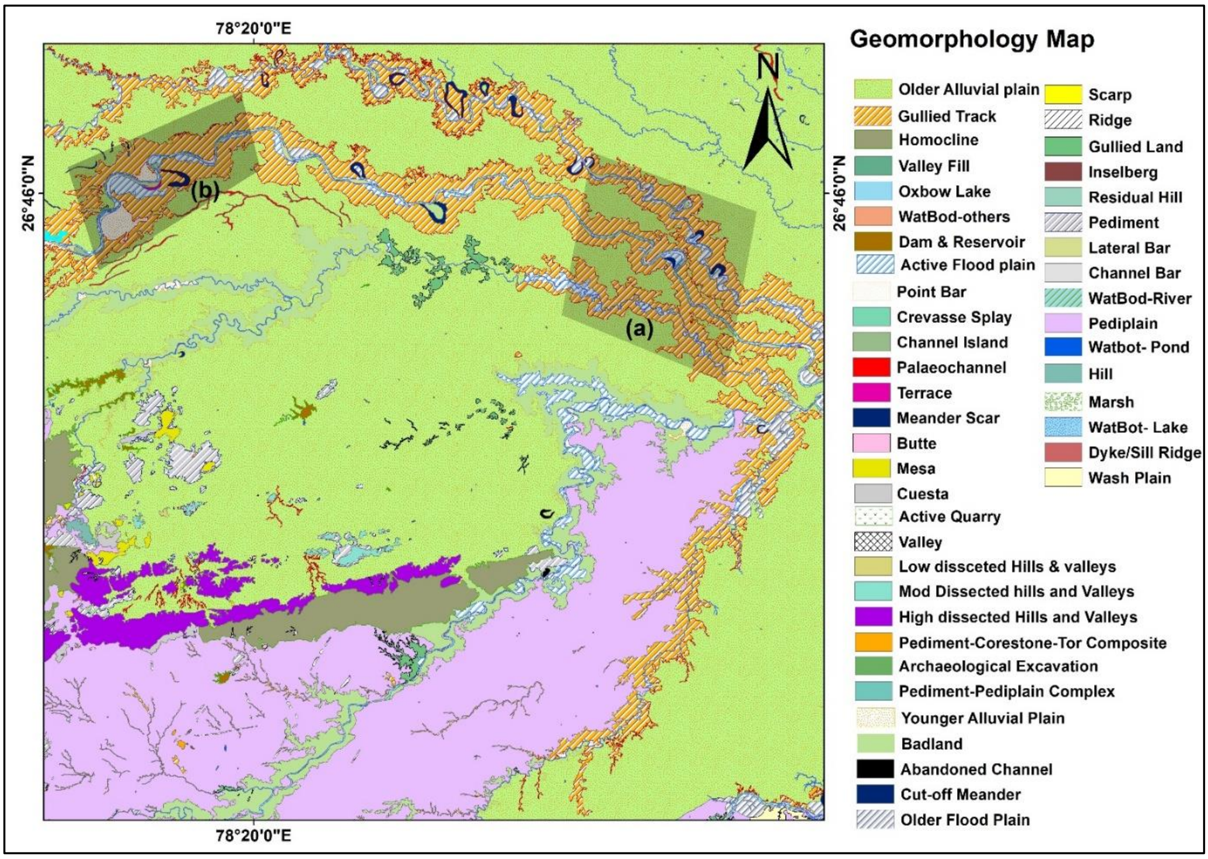


Figure 2-2: Geomorphological Map of Chambal badland, (a) covering the main study area of Bhind, (b) covering the area of Rajkhera tested for selection of study area procedure.

2.3 Physiography and Drainage

The study area is part of the lower Chambal valley, devoid of hills or any older rock formations. The entire region constitutes part of the Gangetic alluvial plain. The drainage pattern of the area lying close to the bank of the Chambal river is highly dissected and extremely fine. Here the Badland topography is characterized by forest-type ravine and comprises some scattered vegetation cover. The elevation of the area ranges between 100-200 meters above mean sea level. The main Chambal and Kunwari rivers of the area flow almost east. The Chambal River further joins the Yamuna River and Kunwari joins the Sind, which in turn joins the Yamuna river. Thus, the whole area falls within the Gangetic drainage system (Geological Survey of India- GSI report 1989-1990).

2.4 Geology of the Area

Ravines in lower Chambal valley are the worst example of Badland in terms of land degradation in India. Neo-tectonic activities and the development of south-west monsoon intensity in the late Pleistocene-Holocene are believed as the possible reason for this Badland formation. Due to neo-tectonic activities, the Chambal river has been experiencing many changes to attain its present planform. The followings are the main geological aspects of Chambal Badland.

2.4.1 Pre-Quaternary

The Southwestern part of the study area is covered by Bundelkhand granites which have been more or less peneplain and are crossed by linear quartz reefs along the long fracture plain. On the East-West side of the area, the Gwalior group of rocks rests unconformably over Bundelkhand granite. However, the Vindhyan are exposed toward North-West, overlying the Gwalior group of rocks, with no exposure in the area under study. Alluvium plain cover is encountered toward the North.

2.4.2 Quaternary

The Quaternary sequence in the Chambal ravine is represented by the Older Alluvium and the Younger Alluvium (Table 2.1.).

- The Older Alluvium is divided into the following three formations

  i) **Raipur Formation**- It forms the lowermost exposed unit. The reddish silt horizon is present on the Chambal riverbed and also in bank sections at several places.

  ii) **Kosar Formation**- Kosar Formation overlies the silty horizon of the Raipur Formation and the settlement is unconformable. The maximum exposed thickness of the Kosar Formation is approximately 40 m (between 110 and 150 m above MSL.)

  iii) **Gyanpura Formation**- This Formation is underlain by the Kosar formation. Their contact is unconformable. The maximum thickness of this Formation is about 20 meters. It is a fluvial terrace deposit of the Chambal River which consists of feebly oxidized sandy silt.

- The Younger Alluvium is represented by Chambal formation only

This is the youngest Formation exposed in the area. It consists of channel and flood basin deposits of the Chambal and Kunwari rivers and their tributaries. The channel deposits are coarser in nature and comprise of pebbles (mainly lime concretions) and coarse to fine sand, whereas the flood basin deposits are comparatively finer and comprise mainly of silt and clay. All these deposits are loose to semi-consolidated and oxidized. Lime concretions have not developed in this Formation. The maximum thickness of the Formation is about 3 meters. The exposed thickness of the Older Alluvium is 40 meters (GSI, 1989-1990). In the lower part of the exposed Older Alluvium high energy deposits viz., conglomerate and gravel beds are present, inter banded with red silt horizons and sandstone lenses/layers. These deposits are present as narrow strips along rivers and canals. During the dry period channel deposits e.g., sands of point bars get reworked due to wind action forming ripple marks (wind) on the surface. These deposits are fossiliferous. Vertebrate mammalian fossils of the Upper Pleistocene age are being reported for the first time from this region. In the upper part of the Older Alluvium, sandy silts and clays of flood basin deposits are present. In this part, a 1.8-meter-thick reworked ash bed is also found, which points to a late Quaternary volcanic activity. The ash bed is being reported for the first time from the Chambal basin.

Table 2-1: Geology of the Chambal Basin

Quaternary	**Formation with Age**	**Lithology**	**Thickness (m)**	**Environment of Sediments**	**Associated Fossils/Stone tools Artifacts**	**Associated Landform elements**
Younger Alluvium (Holocene)	Chambal formation	Loose to semi consolidated pebbles, sand, silt, and clay unoxidized	8-10	Channel and flood basin deposits	Few fossil bones of Mammals (Petrification poor) and earthen pots and brick pieces	River channel, point bar, meander scar, natural levee, flood basin
Older Alluvium (Upper Pleistocene)	Gyanpura Formation	Sandy silt with rare lime kankars, feebly oxidized	15-20	Flood basin deposits	Not traceable	Fluvial terrace, palaeo levee
	Kosar Formation	Reworked volcanic ash, Sandy silt with lime concretions, Sandstone, Gravel bed, Silt and clay, Conglomerate	40	Channel and flood basin deposits	Rich in vertebrate mammalian fossils e.g., Bovini, Boselaphus, Equus, Cervus, Elephas etc., Shells of molluscs also present in abundance. Some stone artifacts also present	Fluvial terrace, (palaeo flood plain)
	Raipur formation	Red silt with lime nodules Highly oxidized	Base not seen	Flood basin		

2.4.3 Recent Geological set-up

Geologically the Chambal area is covered by Proterozoic sedimentary rocks and Pleistocene plus recent river deposits. The lithology of the area comes under the thick alluvium of the Indo-Gangetic plain formed during the Pleistocene, which is vulnerable to erosion. The area is mainly dominated by Vindhyan sandstone (Kaimur sandstone) (Dwivedi & Ramana, 2003), which affects around north to south, but in the north and north-eastern part, its direction gradually changes and becomes parallel to the Chambal river (Pani et al., 2005; H. S. Sharma, 1979). Four major ranges with massive sandstone beds from east to west belong to the lower Rewa, upper Rewa, and lower Bhander formations. The predominant geological formations exposed in the region are Rewa and Bhander of the upper Vindhyan range. This ravine land is encircled by the river Yamuna, Chambal, along with its other tributaries. In the north along with the Chambal River, alluvium contains clay, silt, and gravel of various thicknesses, up to 200m maximum thickness, as reported in 2005 by Pani et al., 2005. The soil type of study area is broadly divided into (i) sandy loam to loam soil with low phosphorous and salt content, and (ii) clayey loam soil with low phosphorous and salt content. Recent and sub-recent deposits spread over the biggest part of the area. Because of their loose nature, the soil is highly eroded by water and wind, forming an intense network of gullies that are deeply dissected and unsuitable for agricultural purposes.

2.4.4 Paleontological Studies

Studies of the fossils show the presence of the following fossils:

1 Horn core, astragalus, limb bones, post-cranial bone metatarsal (proximal end), teeth. Pelvic girdle and scapula of Bovini (Bos or Bubalus).
2 Molar of Equus.
3 Hoof and teeth of Cervus (Antelope).
4 Mandible of Boselaphus.
5 Tusk end of Elephas (Photo 18).
6 Canine of Hippo.
7 The carapace of Turtle.
8 Tooth of Gavialis.

2.4.5 Sedimentology

The area in the lower Chambal valley is covered by thick sandy-loamy alluvial sediments deposited by the Chambal river, Yamuna river, and their tributary rivers Kunwari and Sind river. Table 2.2. is based on sediment analysis on 15 samples of sediments from the Chambal river, Yamuna river, Kunwari river, and Sind river by GSI (Geological Survey of India). In this analysis, sediments of the Chambal river are found as coarser than sediments of Yamuna and Kunwari as it was better sorted than sediments of Yamuna or Kunwari. Sorting of sediment is a degree of dispersion of a grain size distribution. Coarser sediments are more unstable, and it is more vulnerable to erosion by water currents.

Table 2-2: Shows a comparative study of the characteristics of younger alluvium of the different rivers.

Chambal	**Yamuna**	**Kunwari**	**Sind**
Coarser than the sediments of the Kunwari and more or less the same as the sediments of Yamuna	Same as the sediments of Chambal i.e., coarser than the Kunwari and better sorted than the Kunwari and Sind sediments	Sediments finer than the Chambal, the Yamuna, and the Sind sediments	Relatively coarser sediments than the sediments of the Kunwari
Sediments better sorted than the Kunwari and the Sind sediments	Symmetry in coarse and fine fractions of the sediments	Relatively less sorted sediments, than the Chambal and Yamuna sediments.	
Sediments show perfect symmetry in coarse and fine fractions of sediments		Perfect symmetry in coarse and fine fractions of sediment.	
Sediments transported and deposited by constant velocity current	Indicative of constant velocity current at the time of deposition	Constant current velocity at the time of deposition	

2.4.6 Mineral Composition and Geology

In the report by Geological Survey of India (GSI, 1989-1990), Quartz was detected in a major amount, Muscovite (Sericite) composition was less than Quartz, but it was also in good amount, Chloride was found in considerable amount and less than Muscovite, whereas Calcite and Felspar were observed in small amount and trace amount respectively. The test was performed on the sample collected from the Chambal river area, which contains Clay/Loess ash samples.

Geological Map is based on the geological surveying of the Chambal river area by GSI in 1989-1990, (GSI-Geological Survey of India). The location of surveying was based on the toposheet number, the area of research in this study is part of the Bhind region which falls under the Toposheet no.- 54J. Figure 2-3 shows the geological map of the ravines area in Bhind and Morena along the Chambal River. Most of the area is covered with younger and older alluvial plains as well as sandstone and conglomerate.

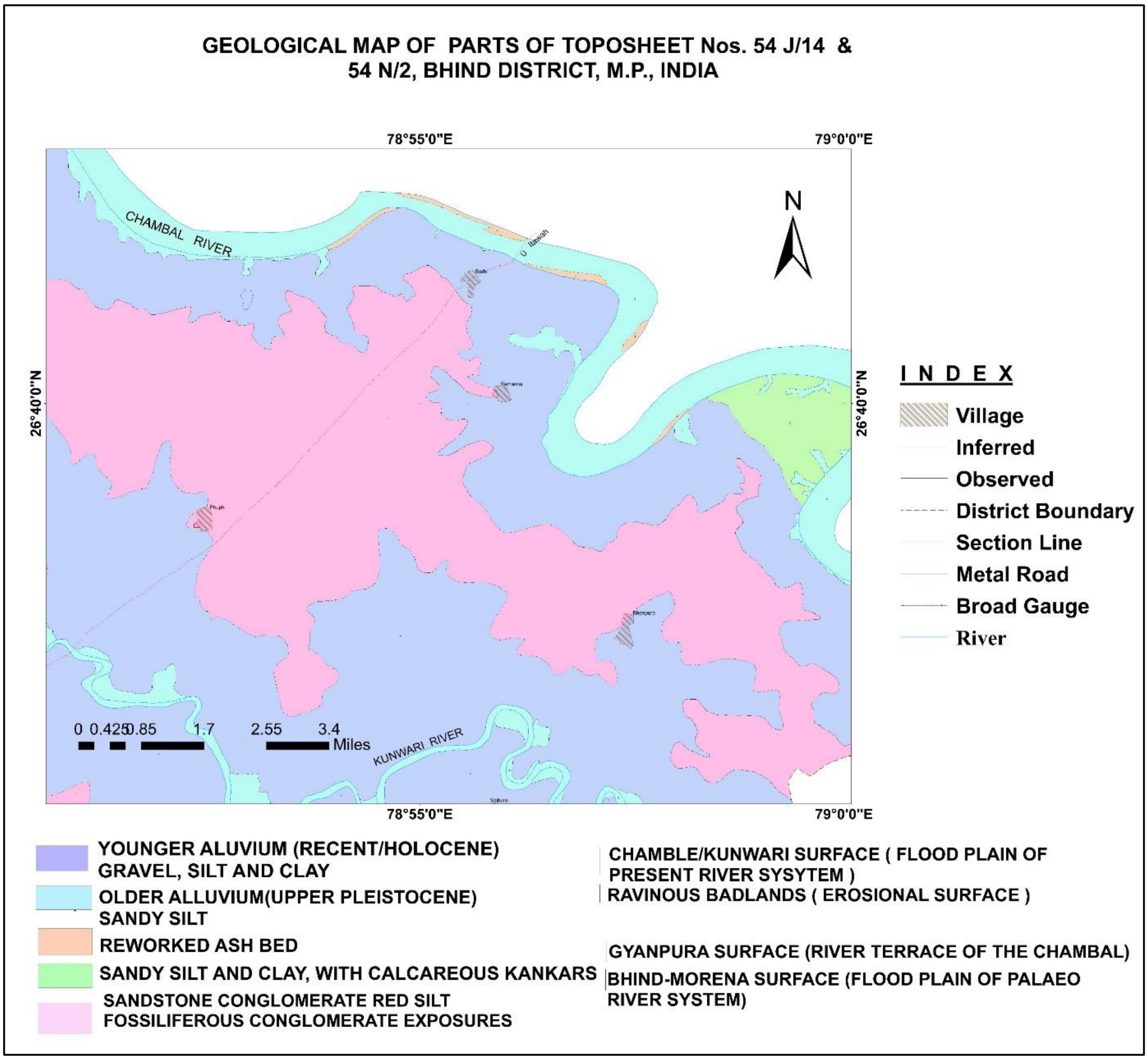


Figure 2-3: Geological Map of Chambal ravine in Bhind

2.5 Climate and Meteorology of the area

The study area experiences a subtropical arid to the semi-arid type of climate. During the peak of hot summer, the mercury reaches more than 45°C mark and approaches almost 3°C during cold days of winter. The monsoon is active from the last week of June to September. The average annual rainfall is 760.4 mm reported in 1990, which is now decreased to 685 mm in recent time. Humidity is generally high during the South-West monsoon season and decreases after the withdrawal of the monsoon. The humidity also used to increase by north-eastern air coming from the Bay of Bengal. The driest part of the year is the summer season when the afternoon relative humidity is less than 20 percent (District Gazetteers-Datia District). The average wind speed of the study area is about 4.65 m/s. Extensive soil erosion occurs because of gullies and ravine formation during the rainy period, affecting the region's overall development. It has been noted that erratic rainfall initiates headward erosion, and it is prominent in both the untouched ravine lands as well as the leveled lands of Chambal valley in a very short time

2.6 Flora and Fauna

Flora in the study area is mainly covered by patches of thorny vegetation (Pani, 2020a). However, it is devoid of any natural forest. A major part of the area is covered by alluvium and is put under cultivation (excluding ravenous Badland), and crops like mustard, wheat, pulses, etc. are grown. In ravenous parts, the occasional development of xerophytes plants can be seen. The area does not support a rich wildlife diversity. Presences of blue bulls, foxes, peacocks, etc. are reported. In the Chambal River, alligators, crocodiles, turtles, fishes, etc. are abundant.

2.7 Environmental degradation in the study area due to ravine and gully erosion

Land degradation is one of the biggest environmental challenges for human beings. Providing sufficient food to each person in society or the entire population depends on the good condition of the land and land fertility. Plus, the loss of biodiversity due to land degradation greatly pressures the world's ecosystem. Their extent to support vital services is decreasing in this ever-growing world’s need time (Millennium Ecosystem Assessment (Program), 2005). Quality of environment and ecological risk connects to socio-economic condition and political dynamics (Salvati et al., 2015). Land degradation caused by ravine and gully erosion is a threat to both society and the environment. From an ecological perspective, gully erosion-related consequences include desertification (Salvati et al., 2015), sedimentation in the water bodies (Fox et al., 2016; Sharda & Ojasvi, 2016; Swarnkar et al., 2018; X. Zhang et al., 2018), loss of aquatic biodiversity due to sedimentation, flooding, and destruction of agricultural land (Kirkby & Bracken, 2009; Torri & Borselli, 2003). Environmental issue because of land degradation desertification have implications in the world and is the major issue at the United Nations Convention to Combat Desertification (UNCCD), the Convention on Biodiversity, the Kyoto Protocol on global climate change and millennium development goal (UNCED- United Nation Conference on Environment and Development, 1992) (Madeley, 1992).

However, the environmental degradation, particularly in this study, is mainly related to three aspects, loss of soil and valuable nutrients for plants by gully erosion (Pani, 2016, 2020a), Hydrological function disturbance (A. Sharma & Tiwari, 2014), and sediment loads in the water bodies (Pani & Carling, 2013).

- **Sedimentation**

Sedimentation is a very common problem in several ecosystems, but gully erosion causes sedimentation to induce hazards for land fertility and aquatic system disturbances. In the water bodies, sediments change their temperature, pH and water depth by shallowing the surface, which ultimately causes flooding (Merritt et al., 2003; Poesen et al., 2003).

- **Hydrological function:**

Ravine and gullies often cause big trouble with increased drainage and accelerated aridification processes (Sahoo & Jain, 2018; Valentin et al., 2005). Poesen et al., 2003 and other studies estimated 10-94% of total sediments in a watershed are by gully erosion. In the current study area, gullies often cause condensation of the runoff into narrow channels, preventing the rainwater and flood water from irrigation, ultimately resulting in loss in agriculture (Poesen et al., 2003).

- **Fertility of Soil and Agriculture**

Agriculture is a primary livelihood tradition in most parts of India. The semi-arid regions are relatively less developed in the country because almost 80% of rural people are dependent on agriculture (figure 2-4, agriculture in ravine). The agricultural process depends on soil fertility and water drainage system, which are destructed by gully erosion in ravenous areas (Borrelli et al., 2014; Valentin et al., 2005). The condition of the soil profile has become very poor due to erosion. In the Chambal ravine, gully erosion process has left behind sandy or stiff clay with poor water retention capacity in the soil, thus it was classified as non-arable land by KRISHI of the Indian Council of Agriculture Research- ICAR by Uthappa et al., 2016). Further in this report, the uneven land profile was classified into three parts: ravine top or hump, slope, and bottom/bed.

Figure 2-4: Agriculture land in Chambal badland, exist with ravine.

2.8 Socio-economic degradation in Chambal ravines

The administrative areas along with the Chambal ravines are densely populated and mostly rural, where people are economically poor. According to a report by Madhya Pradesh Government, Chambal has witnessed long-term drought, occasional excessive rains, and food shortages (GoMP 1996, 118–119). However, the inhabitants of the area belong to multiple religions and castes with various cultures and traditions. Other than agriculture, some populations also work as carpenters, weavers, labor-wage earnings, etc. for livelihood (Pani, 2018). The literacy rate in this region is extremely low, about 38% (Chaudhuri & Gupta, 2009). Chambal is also well-known as Beehad, which means extreme, and the extreme ravenous land favors several crimes in this area, especially since Chambal is defamed for dacoits (Armed

Robber). Dacoity gained such harbor here, because of favorable geographical/terrain conditions. The ruggedness of the topography with maze-type gully network, and the less human interference because of less agricultural activity in harsh environments have all helped the dacoits a safe haven away from the catch of the law (Haigh, 1984).

The socio-economic status of the Chambal region can be defined as a rural area in the plain with a dense population surrounding the Badland and within it in small patches of land that are dominantly used for subsistence agriculture. Figure 2.4 shows the image of the Chambal ravine in 2016 where agricultural land exists with a ravine that is 10-20 m in height. Generally, the land faces fragmentation due to growing population strength and less capability for profitable land utilization. Less opportunity for other employment, adequate infrastructures, and a sense of isolation from other cities are also common problems. Moreover, rain-fed cropping is somewhat uncertain and impractical because of constant droughts, but excessive rains also sometimes lead to crop loss and food shortages (GoMP, 1996). Though the situation has started to improve slowly since the 1970s, in the 1980s ravines reclamation program is ranked as a high national priority, making India the third world's leading soil conservation program country (Haigh, 1984). Under this program, a series of reclamation activities were undertaken to improve the land condition by several methods, to provide an agricultural facility, infrastructure, medical, education, and other facilities, which can make inhabitants in getting a proper benefit from the resources available. As the development activities have been started and after a strong operation in the 1980s by the government, the problems of dacoits now do not exist (GoMP 2007).

2.9. Ravine Reclamation Projects

Ravines reclamation was rated as one of the main national priorities during the 80’s when the formation of gully became too conspicuous to be missed, especially in Chambal ravines, and India had the third world's leading soil conservation program (Haigh, 1984). Several ravines reclamation programs have been started for Chambal Badland by the government from time to time (Pani, 2016). But the policymakers and planners assumed it was a one-time function, so they fixed the budget and involved mostly mechanical actions. The activist constructed field bunds and property bunds and started leveling the ravine land where the loose soil hold measurement was absent; and because of inappropriate construction of tanks at the improper site, the condition of land became worse despite spending millions of budget (G. P. Verma et al., 2018). As a result, the gully networks and ravines have become more deep and intense and it is still growing ahead (G. P. Verma et al., 2012). Here the stage of gully erosion is to be dealt with advanced and tested technology by the researchers. The basic requirements for effective ravine reclamation actions need to research on (a) various observations and measurements of gully erosion intensity and effect in that area, (b) to implement a robust program of geomorphological, geological, hydro-meteorological monitoring to have area-specific information for any decision making, (c) Monitoring of masonry check dams for gully erosion restrain and ravine reclamation in deep ravines bed, (d) Study on the requirement of various crops can be grown on soil after ravine reclamation.

2.9.1. Previous efforts made on ravine reclamation

Before the Independence of India, the seriousness of the ravine hazard was recognized by the ruler of the erstwhile state of Gwalior (Now in Madhya Pradesh, MP state) in the twentieth century, together with international agencies like World Bank (WB) and European Union (EU), etc. After Independence, the government of Madhya Pradesh (MP) implement several ravine reclamations projects for Chambal Badland (Table 2-3), such as Chhonda project (1955-56), Bagchini project (1955-56), Nayakpura Project (1956-57), Deori Hingona (1959-65), Jawasa Project (1962-70) and Dimini- Chandpur Project (1967-68). These projects were aimed to treat the 9080-hectare land in the first five years. Under these programs, an area of 9,080 ha was treated from the first five-year plan; within itself, it was categorized as 3,100 ha of land for ravine reclamation and 5980 ha of land for ravine afforestation at the cost of Rs. 44.23 million (G. P. Verma et al., 2018). From 1950 to the present time, the government of India has invested heavily in ravine reclamation (Tomar et al., 2015). The soil conservation plan consumed 16 billion INR (INR-Indian Rupees) between 1969- 1990 (Kerr & Sanghi, 1993).

Chambal multipurpose Hydel project also joined this line and was initiated by a joint venture of the MP and Rajasthan state governments to enhance Chambal River's irrigation potential by constructing Dams, canals network, and rectangular field by leveling ravine land by the bulldozer. However, the leveling of land without measurement of soil hold made the problem in this plan. The World Bank launched a project in 1980 for aerial seeding of trees species on 82,000 ha of land under the Chambal area, but this plan was not a success also because seeds couldn’t rest on the ravine slope and gathered in the deep ravine bed where they grew as the thick forest of *Prosopis Julifora*. As per instruction from the government of India, during 1988-1992 the ravine reclamation action was taken forward in MP and UP (Uttar Pradesh state) for Dacoity (Robber) prone area development. In which 476 km of peripheral bund along with tableland treatment of 5229 ha and shallow ravine treatment of 27,776 ha was executed by spending 36.244 million INR in MP. European Union (EU) also funded a project in 1987-1994 the "Integrated Watershed Management Program in ravines of Chambal and Yamuna catchment", it shows land development efficiency by introducing improved high-yield varieties of crop species and introducing tube well irrigation. But it was a costly project, especially the construction maintenance has more requirements; thus, after some years, it gave up because of lack of maintenance.

Table 2-3: Summary of some of the previous ravine reclamation projects

Scheme	Sector	Period	Expenditure (INR, million)
Chhonda project	State	1955-56	44.23
Deori Hingona	State	1959-65	
Jawasa Project	State	1962-70	
Dimini-Chandpur Project	Inter-state	1967-68	
Ravine Reclamation	Central	1970-84	20.120
CADA (Ravine erosion control)	State + World Bank	1976-87	36.244

2.9.2. Recent Ravine Reclamation Projects:

NICRA Project

Indian Council of Agriculture Research (ICAR) funded NICRA (National Initiative on Climate Resilient Agriculture) for research to manage deep ravines for food and environmental security. The main aim of this project is the sustainable management of Chambal ravines and carbon sequestration for climate adaptability. It emphasizes the plantation of native trees and medicinal plants and dozes the path to the inaccessible very deep ravine to enable the plantation of trees. Followings are the other critical evaluation of various works for reclamation and control of deep ravines also executed under this project.

1) Greening ravines

2) Earthen gully plugs
3) Steep sides and point tops
4) Checking of gully advancement
5) Shaping of gully side tops
6) Extent of land shaping
7) Multi-step leveling system technology
8) Performance of Gabions
9) Steep bed of the main gully
10) Appropriate Vegetation cover
11) Runoff collection and recycling
12) Appropriate land use plan

- **Anicut and Afforestation**

The forest department of the MP government started a project in 2007-2008 on ravine reclamation of the Chambal region by afforestation. It comprises a team of foresters, local farmers, and village leaders. In this project, the construction of anicuts or dams was taken forest land of Morena district and Bhind district (study area) to protect the farmer's land against the formation of ravines to increase crop productivity and cost benefits.

2.9.3. Approaches should be taken in ravines reclamation

- **Watershed-based management**- ravine growth and formation are a function of water runoff. Thus, the management of rainwater on a watershed basis can be an important step in ravine growth control.
- **Tableland**- The formation of tableland for in-situ water conservation in tableland areas can be a more profitable use of conserved water.
- **Water diversion bund**- A peripheral or water diversion bund should be designed and made between tableland and ravine land to lead the runoff from tableland to a safe place.
- **Treatment of shallow medium and deep ravine-** (a) First is the identification of the main gully, then the bund should be stabilized across the general slope of proper size and across all main gullies. (b) Smoothing of land on both sides of the gully, between two bunds to reduce the slope of the land. (c) Planting of *wild sugarcane (Munj, Saccharum Munja)* grass or vetiver (*V. zizanioides, khus khus)* on the bund to establish it. (d) Constructions should be at an appropriate site, such as a runoff collection pond or tanks.

- **Treatment of very Deep ravines-** Most of the very deep ravines are in lower Chambal valley (study area) where the alluvial soil track and Chambal River channel functions are dominated. The efforts that have been made in the past were not very successful and were expensive. There are no proven techniques for treating very deep ravines, but researchers are making efforts from various contributions in this way.

Chapter 3: Literature Review

3.1 Introduction

Land degradation has been a major global environmental problem throughout all generations (Kumar et al., 2020). Ravine and gully erosion is the biggest culprit responsible for land degradation worldwide (Arabameri, Cerda, et al., 2020; Borrelli et al., 2014), area affected by gully erosion is the most severe and degraded landform (Taruvinga, 2009; Torri & Borselli, 2003). In the gully erosion process, water displaces the upper soil material and forms a deep cut or a continuous depression on the land surface. Its depth is larger than the rill and cannot be ceased by the ordinary tillage process. Ravine is the final stage of gully erosion, generally, ravines have a very high drainage density, are developed in semi-arid and arid regions, and are characterized by several narrow gully channel networks (Ghosh et al., 2018). It can be defined as an erosion channel with a cross-section area of >1ft square (larger than rill) which cannot be recovered by the ordinary tillage process (Poesen et al., 1996). Generally, a region with a larger number of gullies and ravines is called as Badland topography. This phenomenon affects the environment and ecosystem through, Desertification, Flood, fertility loss, and sedimentation (Kirkby & Bracken, 2009; Torri et al., 2012). The process carries a load of Sediments which highly impact the quality and quantity of the water body (Swarnkar et al., 2018). Some case studies like (Kar et al., 2020) also explain the effect of gully erosion on fish resources and faunal/floral diversity of the water body. These phenomena can be considered as both Natural disasters and Natural resource depletion (Magliulo, 2012; Saha et al., 2020).

Lives and livelihood rely on ravines that are under a very harsh and stressful environment (G. Kumar et al., 2020). People's lives there are generally poor and depend on agriculture which is constantly threatened by gully erosion (Pani, 2016). The nutrients of topsoil decline because of gully erosion and the productivity of agriculture reduce (Gayen & Saha, 2018; Hoyos, 2005; Li et al., 2016). its breaks the mechanics of a farming area into several units directly by removing the land within the gully (Kirkby & Bracken, 2009). Gully erosion is a natural phenomenon, but it is always accelerated or enhanced by anthropogenic activities especially deforestation and the clearing of vegetation (Azareh et al., 2019; Ionita et al., 2015; Sidorchuk, 1999). Once a gully system is formed, it tends to grow larger and deeper, which become difficult and expensive to eradicate (Kirkby & Bracken, 2009); therefore, it is very important to understand the process and dynamics of the gully.

Soil is the most important part of an ecosystem; human life relies on it (Zaman, 2018), especially for food and infrastructure, soil or lands highly affect the quality of human life (Arabameri, Asadi Nalivan, et al., 2020; Fox et al., 2016; Valentin et al., 2005). Today, the restoration of soil properties of degraded land is the biggest challenge among researchers. Therefore, its monitoring and assessment with advanced and efficient technology are essential for gaining the aim of reclamation and meeting the human population's needs. Remote sensing provides accurate spatial information about the land and other objects on earth (Avtar et al., 2020; Pani & Mohapatra, 2001). With the advancement in this technology, like the availability of data in various resolutions and updated information about soil loss dynamics, remote sensing has become the most accepted tool in the last two decades (Sepuru & Dube, 2018). Many remarkable works have been done in the last few decades regarding this field; (Bauer, 2020) also mentioned in his paper, the history of remote sensing and its increasing demand in the field of environmental science. Sepuru & Dube, 2018 described in their review paper about the progress of remote sensing techniques in soil erosion mapping, which also shows the progress of technical advancement in Gully erosion monitoring. However, many studies have made efforts to describe the aspects of gully erosion assessment using several technologies from time to time which needs to be analyzed deeply to understand the ideal methodology for gully erosion monitoring. The current study is a literature review on the use of several technologies for gully erosion assessment, focusing on the popularity and dominance of remote sensing and machine learning. It will provide an overview of the utilities of these techniques and their complexities.

In the past three decades, many studies have applied the remote sensing data fully or partially for ravine and gully erosion assessment in many ways. This study aims to synthesize and summarize the comprehensive review of methodologies applied for Ravines and Gully erosion assessment using satellite remote sensing, with special attention to new technologies taking place during the past years. It will also focus on the Pros and Cons of different methodologies.

3.2 Gully erosion process and formation

The formation of gully erosion is initiated by the dynamics of hydrological bodies, where water channels deeply cut the soil and erode the pre-existing uniform land surface into rectangular or V-shapes in cross sections (Kirkby & Bracken, 2009). In the beginning, the formation of the gully channel is speedy and the morphological characteristics are not stable but get stable very fast within a short period of its lifetime (Kosov et al., 1978; Sidorchuk, 1999). Kosov et al., 1978 stated that the initial gully process takes only 5% of its lifetime other 90% of its lifetime spend in gully length, gully area, and gully volume. The intense beginning stage of gully formation is controlled by hydraulic and thermal plus mechanical movement of water on the soil surface, also called thermoerosion; in the last stage, sediment transport is the main process at the bottom of the gully. Gullies are generally isolated; it is an advanced stage of Rill erosion and the initial stage of ravine formation. Rills get widened and very deep, which cannot be recovered by any tillage operation or cannot be crossed by any farm equipment (Kirkby & Bracken, 2009; G. Kumar et al., 2020; Pani, 2016). Hundreds of meters can extend in a single large storm across an apparently pristine area (Tucker et al., 2006). Continuous undercut and resulting collapsing of gully head triggers the upslope extension of most of the gullies, but sidewalls slumping and collapsing contribute a higher proportion of soil loss. (G. Kumar et al., 2020) Gully may start from any depression, such as cart tracks and cattle trails if neglected for long. The soil instability at gully banks leads to sloughing and cave in the bank slope. As described above, most Indian workers considered the gully erosion responsible for ravine formation. There are various theories for gully erosion processes that fall into two categories. Figure 3-1 shows the Chambal ravine with the initial process of gully erosion around the Bhind region (study area).

3.2.1 Categories of gully erosion processes

- The first category of gully erosion process is an advanced phase of Rill erosion, in which a gully is formed by concentrated flow through several stages. The rate of gully formation primarily depends on runoff-producing characteristics like shape, size, and alignment. This type of gully is observed in moderate to high land slope hill areas.
- The second category of the gully is formed by progressing slope failure or by another mechanism, but it is not the advanced stage of sheet and rill erosion. This type of gully is generally found in the alluvial soil of Ravines. These gullies form on the land with a gentle slope, having a high elevation difference. Land with low vegetation or low organic concentration is easily eroded and transformed into gully or Ravines (Kumar et al., 2020)

Figure 3-1: Gully initial process, Chambal badland, India (study area).

3.2.2 Theories of Gully and Ravines formation

There are several hypotheses proposed for the Gully erosion and ravine formation. The effect of climate and land use theory is one of the most popular hypotheses among Indian researchers. Situations like land devoid of vegetation and organic matter, having loose soil and high rainfall can be the main factor in gully erosion and Ravine's formation. Tectonic upliftment theory is another explanation for this process. Steepening of stream gradient due to tectonic wrap, and deep incision led to the high elevation difference between the riverbed and adjoining tableland, which might be the reason for regressive slope failure and ravine formation. River backflow during flood also greatly increases erosion by wet slip and removal of eroded materials (Ahmed 1973). Aravalli mountain range in the central part of India is a good example of this hypothesis (Kumar et al., 2020). Aggradation and Degradation theory believes that the intensification of monsoon rainfall can also be one reason for this hazard. The polycyclic nature of rain floodplains goes through aggradation and degradation phases, and degradation phases cause the ravine formation. The ravines of the Chambal area of India are a better example of this hypothesis. Oceanic Upwelling theory is based on sedimentological and stratigraphic analysis of facies and sediment dating. However, the western theory is not based on concave riverbank elevation theory, but it is a better explanation for gully erosion and ravines formation in the place situated at the riverbank.

3.3 Gully erosion susceptibility approaches: Various concepts and challenges

Among all the available methods used for gully erosion mapping, remote sensing and GIS data-based assessment methods are the most dominating in the literature and accepted as the most efficient and cost-effective (T. Dube et al., 2017; Zabihi et al., 2018). Figure 3-2 shows the chart based on the number of publications that have used several popular methods. RUSLE, USLE, and Machine learning are the most popular methods in gully erosion monitoring; however, the traditional methods were more in use before 2010 while machine learning dominated in recent decades (figure 3-2.). The problem with the field surveying-based gully and ravines monitoring are time-consuming and expensive processes (Poesen et al., 2003). Similar to the traditional erosion susceptibility map, it is limited to a professional's grip only and is very time-consuming and expensive, giving micro-level area mapping (Gayen et al., 2020a; Sepuru & Dube, 2018). Recently remote sensing and GIS coupled with other surveying techniques, especially machine learning, have been applied in many studies to assess the gully erosion hazard for a large sample area, which is less time-consuming and cost-effective; ensures a high prediction rate (Conoscenti et al., 2013; Pourghasemi et al., 2017). Despite these advantages, it offers vigorous monitoring of a large spatial environmental area without any expensive and intensive field visits. Here, the various method used in gully erosion monitoring and assessment is reviewed and discussed.

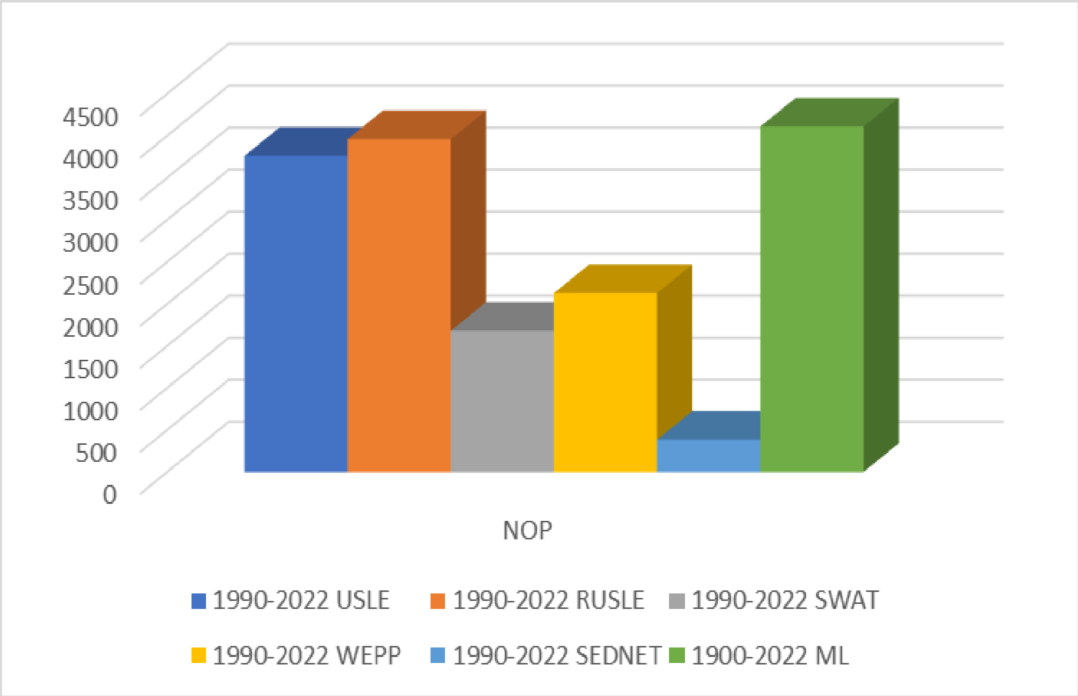


Figure 3-2: Adaptation in methodological approaches in journals for gully erosion susceptibility from 1990-2022

3.3.1 Traditional method

Traditional methods usually applied in gully erosion modeling can be categorized as empirical, physical, and conceptual based on soil erosion (Merritt et al., 2003; Sepuru & Dube, 2018). Empirical is one of the traditional model types is simply based on field surveying, measurement, experimentation, and statistical techniques which can sate the relation between erosion factor to soil loss. It provides the simplest model as it is confined to limited input and criteria (Merritt et al., 2003). The USLE and RUSLE (Universal soil loss Equation and its revised universal soil loss equation, respectively) are the most used empirical erosion modeling, especially in monitoring Rill erosion, the shallow version of gully erosion (Sepuru & Dube, 2018). RUSLE is also widely used in soil erosion rate estimation caused by rainfall and associated overland flow (Zare et al., 2017). However, these models can't give spatial information on the distribution of eroded land, so remote sensing and GIS can be used to manage this weakness (Fistikoglu & Harmancioglu, 2002). Researchers have recently applied the combination of RUSLE, USLE with GIS data and machine learning modeling for better results. Dabral et al., 2008 also applied USLE and ArcGIS and ERDAS IMAGINE image processing software.

The physical-based modeling includes the basic understanding of the erosion process and the law of mass conservation and energy (Sepuru & Dube, 2018). Usually, a large number of measurable parameters with heterogeneity in characteristics of catchment involve in this modeling (Merritt et al., 2003); so, the tested parameter and observed data are often adjusted against each other. Example of physical modeling is SWAT (Soil and water assessment tool) and WEPP (water erosion prediction project), applied in many geographical contexts (Brazier et al., 2000; Laflen et al., 2004; Yu & Rosewell, 2001).

Conceptual modeling commonly is interlinked between empirical and physical based modeling, it includes basic knowledge of the catchment process (Prosser et al., 2001; Sepuru & Dube, 2018); Unlike empirical and physical modeling it doesn't give actual information about erosion processing phenomenon in the catchment (Beck, 1987). Table number 3.1 summarizes all three types of the traditional model, its methods, its outcome, and some publication that applied these models in the study of gully erosion.

However, all the existing traditional modeling techniques are complicated and require large data set. There are always some limitations that can be efficiently managed by adding the facilitation of remote sensing data. The support of GIS tools can provide the evidence and information for gully erosion estimation in limited requirements.

Table 3-1: Description of traditional methods involved in Gully erosion monitoring

Model type	Name of Model	Output	References
Empirical model	RUSLE (Revised universal soil loss equation), USLE (Universal soil loss equation)	Soil erosion	Bhattacharya et al., 2020; Dabral et al., 2008; Merritt et al., 2003
Physical Model	SWAT (Soil and water assessment tool), WEPP (water erosion prediction project)	Sediment characteristics, form of sediment loss	Bera et al., 2020; Brazier et al., 2000; Laflen et al., 2004; Yu & Rosewell, 2001

Model type	Name of Model	Output	References
Conceptual Model	SEDNET (Sediment budget river network)	Gully erosion and Bank erosion process	Beck, 1987; Prosser et al., 2001

3.3.2 Monitoring-based Gully erosion assessment

Observation of the existence of gullies and ravines is crucial, especially their dimensions, dynamics, and controlling factors are essential for monitoring as it determines the gully erosion rate and its effectiveness. This observation is also significant in preparing the gully control measures (Bartley et al., 2020; Frankl et al., 2013, 2021). The idea of preparing the gully erosion inventory which simply records the possibility of occurrence of a gully with their precise outline is already helping efficiently in identifying the problems and in policy making. This assessment can also be done with the help of field surveying, aerial or satellite image analysis, and remote sensing analysis. Studies have revealed the importance of the role of geospatial data in gully erosion monitoring and modeling. GIS has proven itself as a powerful tool in spatial data handling, processing capabilities, and facilitated data analysis (Dou et al., 2019; Hong et al., 2016). For several years, GIS has been used in gully erosion and in many fields (Avtar et al., 2020; Bocco et al., 1990; Conoscenti, Agnesi, et al., 2013). In the gully assessment field, GIS helps in acquiring terrain information and several environmental variables value, the gully affecting factors. Researchers have employed the relationship between the gully affecting factor and the gully erosion process through geospatial data analysis (Arabameri, Asadi Nalivan, et al., 2020; Gayen et al., 2020a; Saha et al., 2020).

The information derived from geospatial data is a basis for performing modeling for gully erosion estimation. The quality of these data defines the accuracy of GESM (Grohmann, 2018). Even advanced technology like machine learning is also based on GIS data, as it affects the model accuracy designed for GESM. However, the observation and monitoring by aerial photography or satellite image are often hampered by environmental factors such as vegetation, rain, or snow cover (Marzolff & Poesen, 2009). Especially the ephemeral gullies, which are highly unstable and time independent, they can fill or disappear over time and is difficult to assess without error in short and infrequent observations (Kuhnert et al., 2010; Nachtergaele & Poesen, 1999). Furthermore, gully assessment is highly dependent on the grid size or spatial resolution of recorded data. Inventories with more details need higher spatial units, which is difficult in data handling and time taking process. Topographic variables and environmental conditions are very important factors in gully erosion monitoring because it controls the initiation and expansion of gully; the growing availability and development of remote sensing imagery with higher resolution and DEM (Digital Elevation Model) are widely contributing in accessing the good quality Gully affecting factors. In recent studies like Raj et al., 2022; Wang et al., 2021; Zhao et al., 2016 rather than systematically mapping the whole area, employing the random points from the area to make the probability of the presence or absence of gully erosion, is more popular (Sidorchuk, 1999). But this method is often associated with machine learning techniques.

3.3.2.1 Satellite and Sensors used for gully erosion assessment

Images by optical remote sensing have been obtained by a range of air-borne and space-borne sensors varying from multi-spectral sensors to hyper-spectral sensors having spectral domains from the visible spectrum to microwave and also the various range of spatial resolution (Y. Xie et al., 2008). Since the characteristics of sensors (spatial, spectral, temporal, and radiometric characteristics) are diverse, the selected sensors are used for specific studies.

i) Optical Remote sensing

For erosion research, both optical remote and radar sensor acquired data have most frequently been applied. Vrieling, 2006 explained that optical-based RS data is widely used in this study because it covers the visible and near-infrared (VNIR) ranging from 0.4 to 1.3 µm, the shortwave infrared (SWIR) between 1.3 and 3.0 µm, and the thermal infrared (TIR) from 3.0 to 15.0 µm of the electromagnetic spectrum. In optical RS, Landsat is widely used data among all because of its wide range of applications and longest history of monitoring of earth from space, so it is the longest time series of data (van der Meer et al., 2012; Vrieling, 2006; Y. Xie et al., 2008). AVHRR sensors have also proven their number of applications in land surface surveillance and environmental degradation as it has a long record of data already accumulated, also relevant to studying climate change. Another advantage is that it is cost-effective and can obtain cloud-free data (Y. Xie et al., 2008).

Goward et al., 2003 find that the IKONOS data is also useful for ‘virtual’ ground measurements for the lower spatial resolution global observatory. However, its high-quality, resolution imagery data, which can be potentially used in erosion mapping, is too expensive to research (Taruvinga, 2009). Quickbird was launched in 2001, which provided high-resolution satellite data. Like IKONOS, it provides very accurate imagery at 60-70 cm resolution by panchromatic band and 2.4-2.8 m resolution by multispectral imagery. It offers a sub-meter resolution. Quickbird's data is beneficial in land asset management (including ravine) and ecology modeling, but it is usually utilized for the study of relatively small areas and local scale only because of its high cost and limited technical parameter. So, for large area studies applying Quickbird would be inconvenient. Some studies like (Dwivedi et al., 1997) state SPOT is better than Landsat TM for gully monitoring, but lace with the low spectral capacity makes it unable to classify the eroded area by outcropping (Servenay & Prat, 2003). Although some literature compares SPOT and Landsat TM (Sepuru & Dube, 2018), Landsat images are the most common data used for soil erosion detection (Luleva et al., 2012). These pixel-based Gully feature analysis only uses surface reflectance, but they can be employed for thematic mapping and quantitative analysis of land erosion (Shruthi et al., 2011). However, it requires in-depth knowledge of the study area and an adequate selection of training pixels (Laliberte & Rango, 2009). Table 3.2 condense the overview of all satellites and sensors and their characteristics commonly used in land degradation research. It also describes the operation time of the satellite and the number of publications that applied these satellite data.

ii) Radar Remote *Sensing*

Apart from optical remote sensing, radar-based data have also been used widely in the study of the deformation of land whether Especially SAR (Synthetic Aperture Radar) is a type of radar, it is found to be very efficient in detecting the erosion feature and its factor (Vrieling & Rodrigues, 2005). It can give a two-dimensional image of a three-dimensional landform, which is ideal for gully and ravine landform mapping. In SAR, the locomotion of the radar antenna is used to be observed over the target region to get the 3D image with finer resolution. The SAR Interferometry (InSAR) has been very significant in providing Digital Elevation Model (DEM), which is used to generate the topographic map generation in gully erosion susceptibility (Rufino et al., 1998; Zebker et al., 1994); however, the quality of these DEM is controlled by imaging quality, spatial and temporal baseline and atmospheric artifacts (Chunxia et al., 2005). InSAR leads to cost-effective data acquisition of all-weather operations for a large area. It can be obtained from single-pass systems and repeat-pass systems (Chunxia et al., 2005). There are some drawbacks that exist with InSAR data processing i.e., phase unwrapping errors, absolute vertical datum errors, linear trend, and planimetric errors (Chunxia et al., 2005; Lu & Dzurisin, 2014). The recent development in SAR is TanDEM-X (TerraSAR combined for DEM). It is an InSAR mission from the German aerospace center (DLR) and EADS Astrium (Airbus Defense and Space) for near-global coverage and 12m DEM (Brosens et al., 2022; Grohmann, 2018). The TanDEM-X is broadly contributing to the studies related to Land degradation, especially gully erosion (Bernini et al., 2021; Bosino et al., 2021; Brosens et al., 2022; Grohmann, 2018; Rufino et al., 1998). Vrieling & Rodrigues, 2005 applied multi-temporal SAR imagery for erosion assessment in Brazilian cerrado. SAR-derived DEM has been found as suitable and used widely used especially in new trending machine learning methods for gully erosion assessment (Arabameri, Pradhan, & Rezaei, 2019b; Grohmann, 2018; A. Sharma & Tiwari, 2014). Combined with a machine learning algorithm (Ahmadpour et al., 2021) applied SAR DEM for gully erosion susceptibility assessment in south Iran. M. Xie et al., 2016 studied the characteristics of SAR for land deformation in the ravines reservoir of China; the study defines the importance of D-InSAR (Differential synthetic aperture radar interferometry) techniques to eliminate the natural errors and the actual movement of the land. Further, the study explained errors in SAR imagery, especially the atmospheric effect that MODIS satellite data can remove. SAR is the most recent sensor launched with sentinel-1C and the most efficient data to study the land twisting and land movement and can be an optimal data source for future research in this field.

3.3.3 Machine Learning based Gully erosion assessment

Studies from the last two decades get many advancements through machine learning technology in gully erosion susceptibility and management. New methodologies in this research area introduce the usage of machine learning and deep learning. Especially in recent years, ensemble machine learning like Random Forest (RF), Boosted Regression Tree (BRT), Artificial Neural Network (ANN), etc. are contributing significantly to gully erosion research. GIS-based machine learning models have been operated for gully hazard susceptibility like Conoscenti et al., 2013; Martínez-Casasnovas et al., 2004 have applied logistic regression model based on GIS data to find the characteristics of susceptibility conditions to gully erosion. Similarly, frequency ratio was employed by (Conforti et al., 2011), weights of evidence (Arabameri, Cerda, & Tiefenbacher, 2019; Dube et al., 2014; Rahmati et al., 2016; Shit et al., 2020), linear regression (Chaplot et al., 2005), conditional analysis (Magliulo, 2012), analytical hierarchy process (ZXakerinejad et al., 2014), classification and regression tree (Geissen et al., 2007; Gutiérrez et al., 2009), multivariate adaptive regression splines (Gutiérrez et al., 2009) and maximum entropy (ZXakerinejad et al., 2014), multi-criteria decision analysis (Arabameri, Pradhan, Rezaei, et al., 2019).

A study by (Zabihi et al., 2018) utilized different variate, GIS-based statistical models, like the weight of evidence, frequency ratio, and index of entropy to measure the spatial distribution of gully erosion in northern Iran. Some studies have approached the Ensemble data mining method, which combines machine learning models to enhance the power of multiple models to get an accurate prediction. Pourghasemi et al., (2017) did the performance assessment of a series of the individual (ANN, SVM-support vector machine, ME- maximum entropy) and ensemble data mining methods (ANN-SVM, ANN-ME, SVM-ME) for gully erosion susceptibility in Iran. This study concludes that the model performs better when combined as an ensemble model. Arabameri, Rezaei, et al., 2018 studied gully erosion susceptibility in Iran, applied three data mining processes- RF, BRT, and MARS and also studied the spatial relationship between gully erosion and geo-environmental variables using a weight of evidence (WoE). Most recently, Arabameri, Asadi Nalivan, et al., 2020, maps gully susceptibility by integrating four models- MaxEnt (maximum entropy), ANN, SVM, and GLM (general linear model). This research integrates the models in two, three, and four ensembles in which all the models achieve an excellent result, but ANN-SVM gave the highest prediction accuracy and was found to be the best model for this purpose in his study area of Iran.

In gully erosion research, Random Forest has gained the most popularity and accomplishment in producing the most accurate GESM. Random Forest is the type of ensemble classifier based on the decision tree. It is very reliable, flexible, and can work with very high-dimensional data (Caruana & Niculescu-Mizil, 2006). Several studies have compared the RF with other machine learning models on various scales and parameters and declared the RF as the most accurate classifier for gully erosion assessment (Arabameri, Yamani, Pradhan, et al., 2019; Avand et al., 2019; Hosseinalizadeh et al., 2019). In recent decades RF has been employed widely and successfully in GESM (Arabameri, Pradhan, Rezaei, et al., 2019; Gayen et al., 2019, 2020b; Kuhnert et al., 2010). (Rahmati et al., 2017a) also, evaluate the different machine learning models and compare the performance of seven state-of-the-art machine learning models to survey the occurrence of gully erosion in Iran, where RF shows the best performance. (Saha et al., 2020) delineate the most severe gully erosion susceptibility area in eastern India with the use of machine learning techniques like- Random Forest (RF), Gradient Boosted Regression Tree (GBRT), Naïve Bayes Tree (NBT), and Tree Ensemble (TE); the remote sensing data sources applied in this study was ASTER DEM, Landsat 8, and Google Earth images. Both studies depict that the RF is the best and most accurate prediction-performing model for both threshold-dependent (e.g., efficiency and kappa coefficient) and threshold-independent (e.g., AUC) approaches.

3.4 Methodological evolution in gully erosion assessment

The evolution in technology and methodology for gully erosion assessment through the decades came up with several advancements and complexity. From Aerial photography to hybrid machine learning methodology, studies from the last few decades show gradual development and many diversities in the techniques applied for Gullies and ravine land monitoring. The era from 1991-2000 and before that, gully erosion and a gulling phenomenon were commonly assessed by the traditional methods (Beck, 1987; Brazier et al., 2000); sequential photography, and orthodox photogrammetric techniques (Daba et al., 2003; Dymond & Hicks, 1986; Poesen et al., 1996); which are contemplated to have high potential for data extraction for continuous monitoring (Martínez-Casasnovas, 2003). However, from the Decade of 90s, remote sensing and GIS were also profoundly used as a continuous data source for soil erosion research (ZHANG, 1997; X. Zhang, 1999) or land use change management (Sommer et al., 1998). The most common satellite data sets were Landsat 1,2,3- MSS 4,5-TM (thematic mapper), SPOT 1,2,3-HRV, SAR (Synthetic Aperture Radar), etc. Venkataratnam & Sankar, (1996), in their study, also proposed remote sensing as the most compatible and efficient tool for land degradation monitoring and management in a country like India, suffering from a large area of Ravenous land. Especially in satellite data, DEM (digital elevation modeling) has been the most common and useful domain in most of the studies.

Radar Remote sensing-based Digital Elevation Model is the most common and efficient to provide topographic information. In the late 90s and early 20s visual interpretation from aerial photography became more advanced with Digital photogrammetry, which acquired dense 3D geometric information of the real-world object. This technique has been applied in many studies (Daba et al., 2003; Frankenberger et al., 2008; Martínez-Casasnovas, 2003; Marzolff & Poesen, 2009). On the other hand, remote sensing data in this decade enhance by the launch of new sensors and satellite such as- Landsat 7-ETM (enhance thematic mapper). Visual interpretation upgraded with the inception of UAV (unmanned aerial vehicle) and the launch of Landsat-8. Then in the recent decade from 2011- 2020 machine learning based gully erosion modelling dominates the research community. Researchers have also tested Machine learning combined with traditional methods (like USLE and RUSLE) (Gayen et al., 2019; Roy et al., 2020), or with statistical modeling, etc. to produce a more accurate GESM (Arabameri, Cerda, & Tiefenbacher, 2019). Machine learning and deep learning are observed as the latest and most efficient methods for accurate gully erosion susceptibility modeling. Figure 3-3 presents the evolution in three decades in the methodology applied in gully erosion research. Traditional methods show more superiority in the first decade (1990-2000). In the second decade (2001-2010) traditional methods were based on GIS data sources, while in the third decade, Machine learning became more prominent in all aspects of gully erosion assessment research, especially in the last two years (2020-2022); machine learning has gained most dominance.

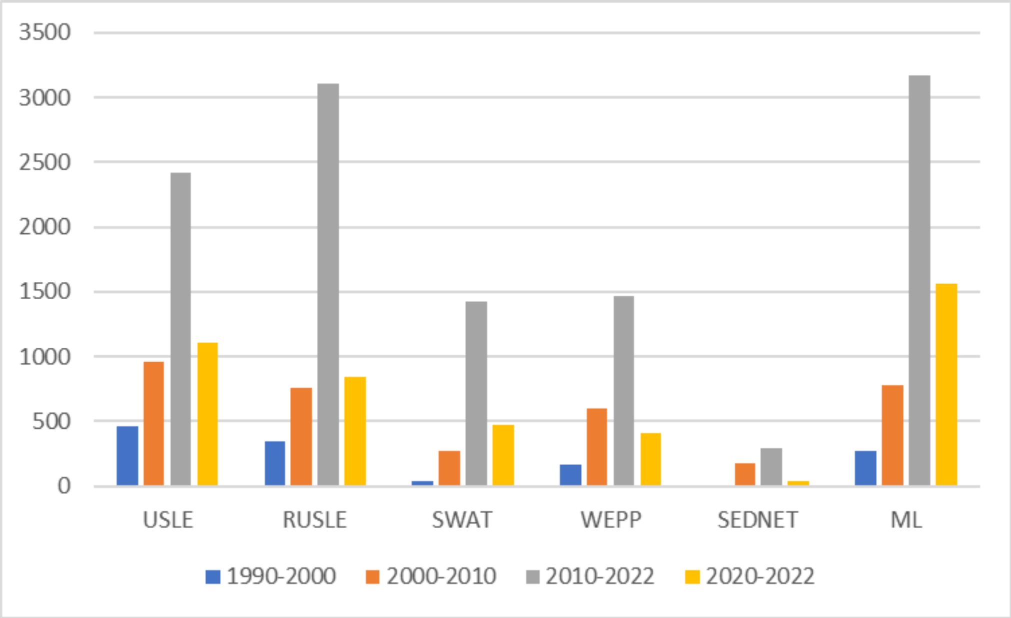


Figure 3-3: Methodological evolution in the last three decades and last two years

3.5 Current Scenario and future scope of Gully erosion assessment research in the world and India

Land resource conservation is a fundamental need of this generation to fulfill the basic needs of humans, like food, shelter, livelihood, etc. Life relies on land; it supports diverse ecosystems and environmental patterns. Although it is often vulnerable to erosion and degradation, water-induced land degradation is one of the most prominent natural hazards. Ravine or gully erosion is the best example of land degradation by water. Gully erosion is a natural hazard destroying cultivated land and affecting other related natural resources in many parts of the world and hence it is the burning topic of concern among world leaders and researchers. Ravine formation and gully erosion are very complex phenomena, the related study requires a series of data with precise topographic information. In the last few decades, research in this area has attained many technical advantages, especially with the help of remote sensing and GIS data facility; the parameter in gully erosion research has been enhanced and expanded.

The application of remote sensing is found as the most useful technique in land resource assessment. In its 50^{th} century of work in environmental monitoring, methodologies encircle remote sensing developed with many advancements and diversity. From traditional method to Aerial photography to machine learning, the studies from these last three decades reveals the complexities adapted in methodologies through remote sensing. Earlier traditional methods (Empirical, physical, and conceptual models) were in trend for land erosion monitoring, although all these three methods have their own input, output, and limitations. The use of these three traditional methods can estimate the land erosion with sediment loss and its characteristics and hypothesis of the process governing the system in the hillslope and catchment area, respectively. It requires a basic understanding of the erosion process and law of mass conservation and energy in physical-based models, field surveying, statistical measurement, experimentation in the empirical-based model, and concept of catchment process in the conceptual-based model. Still, these traditional methods are bound with many limitations like, it is not able to give the actual spatial information about the distribution of eroded land and the details of the erosion process, also sometimes, it is time-consuming and costly (Fistikoglu & Harmancioglu, 2002). However, these limitations are now getting overcome with the help of remote sensing and machine learning techniques. Literature from recent decades is evidence of machine learning and the deep learning era. In the last few years, several methodologies have been introduced by the researcher, including the use of geospatial data and machine learning algorithm methods in many ways. Individually Random Forest (RF) is found as the best performing model for gully susceptibility. The hybrid methodology is also in trend. It is the integration of more than one methodology which leads to very high accuracy and significant outcome. However, all the mentioned techniques are bound with some limitations; only observation-based gully erosion estimation always faces the matter of accuracy and validation and is also expensive and time-consuming, which can be adjusted with a combination of satellite data and DEM. Satellite image limitation is not giving an accuracy of some hidden features and processes behind gully erosion which can be improved with the help of DEM, especially SAR DEM. Studies with the SAR data produce offset errors, but it is possible to correct them with the help of GIS tools. Challenges with machine learning and hybrid or complex methodologies are limited to expert hands only and bound with the heavy mathematical algorithm. Analysis of various research depicts that the challenges lie with all these technologies, leading to the development of more efficient methodology and techniques.

Due to its consistent risk to humans and the environment, it is a constant research topic worldwide. Many studies are dedicated to making an efficient and accurate model for gully erosion susceptibility, particularly in gully-affected countries. Figure 3-4 presents the map of the world and countries which is significantly affected by gully erosion and contributes to the research related to gully erosion assessment. Figure 3.4 shows the number of publications (NOP) in several world countries. In this list, China, India, Iran, Italy, and South Africa are extremely suffering from gully hazards and investing much research in gully erosion monitoring and mitigation. Though most of these researches have focused only on gully erosion susceptibility mapping with high accuracy, there is still lacking study regarding gully development rate and gully erosion-fill volume change estimation for example- Arabameri et al., 2018; Arabameri, Pradhan, Rezaei, et al., 2019; Conoscenti, Angileri, et al., 2013; Pourghasemi et al., 2017; Rahmati et al., 2017; Shit et al., 2020. Similarly, in India also, most of the work has been done for Gully erosion susceptibility and only in eastern India. In past decades attempts have been taken to estimate the gully erosion rate in India, but it was done with the help of the RUSLE equation, which determines only the erosion by Sheet and Rill erosion but ignores the gully erosion (Rowlands, 2019).

India has one of the most extensive Badlands affecting 3.97-million-hectare cultivated land in which the Chambal ravine is the largest and covers 70% of the total (Upadhyay & Chauhan, 2019), yet the Chambal Badland is devoid of any research regarding either gully erosion susceptibility or gully erosion-fill volume change. Most of the studies in this area such as Pani, 2016, 2020a, 2020b; Pani & Mohapatra, 2001 have particularly focused on the area's environmental condition and socio-economic condition. Studies show no clear idea about the gully development rate and the erosion induces volume change in Chambal ravines (the biggest ravines in India). The Chambal ravine of India is under consideration for reclamation and restoration projects by government and local communities for many decades because of its disastrous effect on agricultural land, livelihood, and economy (Joshi, 2014; Marzolff & Pani, 2018; Pani, 2016, 2020b). The area was a favorite hide-out for criminals until the 1980s. An effective action plan must be taken to improve the area's socio-economic condition and ravine reclamation. For this, the area's scientific information is crucial and should be based on monitoring and assessment of gully erosion. Predicting the possibility of active gully erosion, estimating the volume change in the gully by erosion, and developing an accurate and efficient methodology with the help of advanced technology are the basic and crucial steps of any Land restoration program.

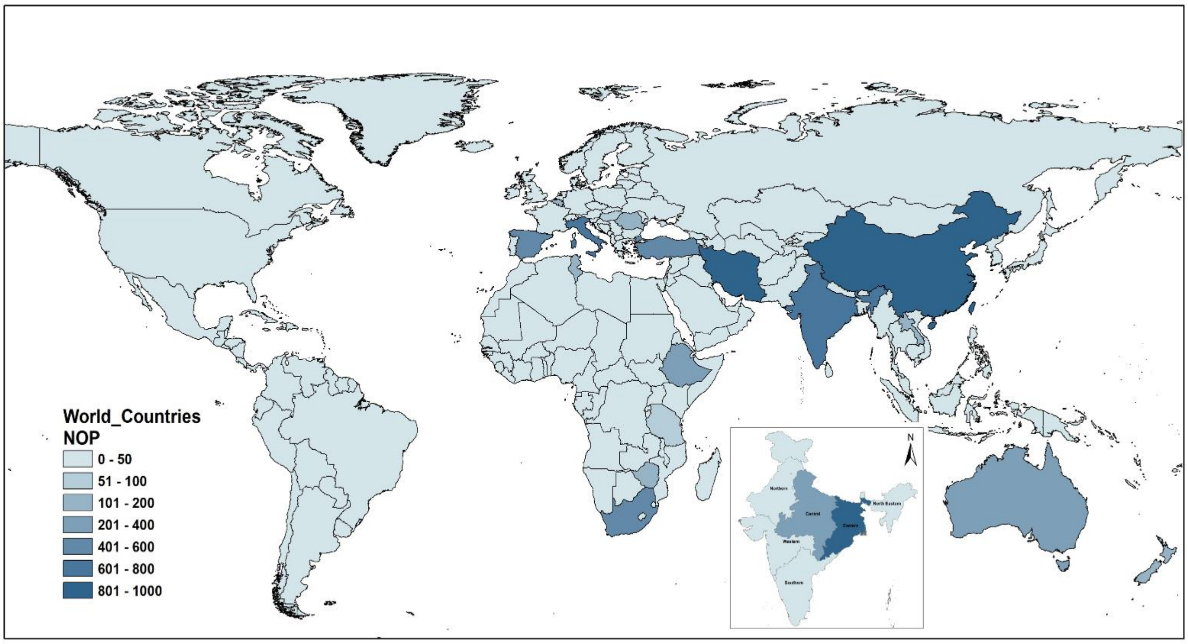


Figure 3-4: Map of the world, the number of publications in gully erosion assessment concerning the country

Table 3-2: The overview of Satellite and sensors and the number of research adapted them in Land erosion Research

Satellite	Sensors	Spatial Resolution	Spectral bands	Spectral Domain	Operation Time	No. of Publication (1990-2022)
Landsat-8	OLI TIRS	30m	11 2	VNIR, SWIR, Panchromatic, CIRRUS, Thermal	2013-Present	1020
Landsat-7	ETM	15m 30m 60m	1 6 1	VNIR VNIR, SWIR TIR	1999-Present	603
Landsat-4,5	TM	30m 120m	6 1	VNIR SWIR TIR	1982-1999	121
Lansat-1,2,3	MSS	80m	4	VNIR	1972-1983	118
Quickbird	Panchromatic Multispectral	0.61m 2.44m	1 4	VNIR VNIR	2001-2015	660
IKONOS	Panchromatic Multispectral	1.0 m 4.0m	1 4	VNIR VNIR	1999-2015	513
NOAA/TIROS	AVHRR	1.1	5	VNIR SWIR TIR	1978-	23
Tera	ASTER	15m 30m 90m	3 6 5	VNIR SWIR TIR	1999-present	113
SPOT-4	HRVIR	10M 20M	1 4	VIS VNIR SWIR	1998-2013	77
SPOT-1,2,3	HRV	10m 20m	1 3	VNIR VNIR	1986-2009	45
IRS-1A, 1B	LISS-1 LISS-2	72.5m 36.25m	4 4	VNIR VNIR	1988-1999	19
IRS-1C, 1D	PAN LISS-3	5.8m 23.5m	1 3	VNIR VNIR	1995-2007	43

Satellite	Sensors	Spatial Resolution	Spectral bands	Spectral Domain	Operation Time	No. of Publication (1990-2022)
		70m	1	SWIR		
Sentinel 1	SAR GRD	10	3	VV VH	2014-Present	2030

Chapter 4: Estimation of gully erosion rate and volume change using TanDEM-X SAR and machine learning models

4.1 Introduction

Land degradation resulting from various natural and anthropogenic activities has been advanced as an important adverse issue threatening global agriculture, forest, woodlands, and land-use practices. Because of their heightened significance and capacity to provide vital services in day-to-day life, land degradation studies have received much attention as a global policy problem (Stavi and Lal, 2015). Effective policy measures and means for sustainable development and conservation efforts on degraded lands were thus planned. Accordingly, Land Degradation Neutrality program has been defined and adopted in the 2030 agenda for Sustainable Development (UNCCD, 2012). The Sustainable Development Goal (SDG) 15 thus promotes “Life on Land” and states: ‘By 2030, combat desertification, restore degraded land and soil, including land affected by desertification, drought, and floods, and strive to achieve a land degradation–neutral world’ (UN, 2019). Nevertheless, the assessment of land degradation, and its prevention and control measures remained an international agenda for a long time (G. Kumar et al., 2020).

Estimates suggest that ~ 10 million hectares of the world’s cultivated lands are the victim of land degradation (Derose et al., 1998; Li et al., 2016). Global assessments of land degradation point to ravines and gully landforms as one of the most important culprits of degraded landform features (Poesen et al., 2003; Sidle et al., 2019; Vanmaercke et al., 2021). By definition, gully erosion is a deep channel created by the concentrated flow of water that removes the surface soil and parent material (Arabameri, Pradhan, et al., 2018; Kirkby & Bracken, 2009). These features in eroded soils produce continuous depression on the land surface slope, often smaller in size than the channel networks with a cross-sectional area >1 sq. ft., however, cannot be halted by the normal tillage process (G. Kumar et al., 2020; Poesen et al., 1996). A ravine is the final stage of the gully erosion process, typically consisting of a complex network of several gullies. Over the past two decades, several studies have inspected the controlling factors of gully erosion and made significant progress in understanding their development (Ionita, 2011; Kou et al., 2020; Poesen, 2011; Yitbarek et al., 2012).

Gullies are often formed in loose alluvial soil and undulating surfaces by a variety of processes: most commonly by uncertain and short-duration high-intense rainfall, subsistence agricultural practices, overgrazing, and deforestation on hill slopes (Rao et al., 2015). Gullies in rural and urban centers cause damage to cultivated lands, roads, buildings, and other infrastructure (Vanmaercke et al., 2021). On a large scale, gully erosion creates a range of trouble, such as desertification, flooding, and sediment deposition in water bodies. They also cause disastrous effects on the ecosystem by reducing soil fertility and imposing huge economic losses (Arabameri, Pradhan, et al., 2018; Valentin et al., 2005; X. Zhang et al., 2018). Because of these adverse effects, gully erosion mapping and monitoring are crucial to land restoration projects. However, traditional gully mapping methods, such as field surveys and topographic contouring,–are time-consuming and expensive in preparing a wide-scale gully erosion measurement. Therefore, other quantitative methods of morphological change prediction systems with high accuracy and efficiency are warranted.

Remote sensing technology, on the other hand, contributes widely and efficiently to the mapping, monitoring, and assessment of natural resources and hazards (Avtar et al., 2019; 2020). The ever-emerging remote sensing and geographic information system (GIS) based topographic analysis with a digital elevation model (DEM) come in handy in quick surveying and erosion estimation; topped with machine learning techniques have been found as the most efficient way of studying gullies at local, regional, and global scale (S. Yang et al., 2019). Starting with the Universal Soil Loss Equation (USLE), Revised-USLE (RUSLE), Brightness Index, and more recent deep learning models, these approaches employing multiple remotely sensed data have been widely implemented to map the gully erosion, analyzing the factors and control of gully erosion, their susceptibilities, and quantifying erosion-fill volume changes with precision (Kou et al., 2020; Pal et al., 2021; Valentin et al., 2005; Vieira et al., 2021, Kumar and Singh, 2021). Very recently, Kumar et al. (2021) have proposed a novel approach to assess future soil erosion under different climate projection scenarios.

Despite the abundant literature on the field, gully erosion volume changes on a catchment level or at a regional and global scale, and predicting the gully volume changes, to our best knowledge, are still uncommon. Primarily, the knowledge gap is because of the lack of availability of high-resolution multi-temporal DEMs. Most commonly, unmanned aerial vehicle (UAV) derived DEMs or Terrestrial LiDAR DEMs are employed to quantify gully erosion volumes accurately (Christian & Davis, 2016; Guan et al., 2021; Niculiță et al., 2020; Perroy et al., 2010; Xu et al., 2019). However, the aforementioned methods have constraints in spatial coverage, limiting a larger-scale analysis. On the other hand, the publicly available elevation models such as SRTM DEM, ASTER-GDEM, and ALOS-AW3DEM do not possess multi-temporal coverage and are lower in spatial resolution. Moreover, though these three products are similar in resolution and acquired at different periods, their source data are different. Thus, they cannot be satisfactorily used as multi-temporal data for gully erosion volume studies. Given their impacts and concerns, quantifying erosion volume and implementing appropriate management strategies are needed that allow the prevention and mitigation of gully erosion in nature.

This chapter aimed to address the gully erosion volume changes and erosion susceptibilities of Badland in Chambal, India using the muti-temporal TerraSAR-X add-on for Digital Elevation Model (TanDEM-X) dataset acquired for 2012 and 2017. The Chambal Badlands of central India is one of the most extensive Badland in the world (Joshi, 2014). This region is one of the most densely populated places in the country, where over 80 percent of the population relies on agriculture-based income. According to estimates, nearly 4,800 sq. km of Chambal valley has been affected by severely dissected ravines (Pani, 2017). Though extensively studied for various environmental aspects, the quantitative geomorphology of Chambal Badland currently lacks a clear understanding of erosion rates and volume change estimates. The specific objectives of the study in this chapter are, therefore: (i) to quantify the gully erosion volume (ii) to develop a framework to predict the gully erosion volumes and soil erosion rate in the area of interest and for future cases (iii) to identify the factors and controls of gully erosion, and (iv) map the gully erosion susceptibilities.

4.2 Data and methods

The present study aims to analyze the morphological changes that occurred in the Chambal ravines of India by preparing the gully erosion volume change estimation and gully erosion susceptibility maps from multi-temporal digital elevation models. The overview of approaches and steps that have been taken to analyze the gully erosion and volume change analysis is shown in figure 4-3.

For this study, TerraSAR-X data scenes acquired from 2012 and 2017 were initially processed with the help of ENVI SARscape to obtain digital elevation models (DEM) at 5 m spatial resolution. Both DEMs (2012 and 2017) were corrected for horizontal displacement and vertical offset using SRTM DEM as reference. The vertical accuracy calculated by comparing the two DEMs and the Survey of India topographic map are ±1.1 - ±1.3 m. The overlapping area of TerraSAR-derived DEMs shown in figure 4-1 between 2012 and 2017 has been selected as the sampling zone for erosion volume calculation. The volume of each pixel in the overlapping area is calculated by the DEM subtraction method. The densely ravenous part of this sample area was divided into two parts 70-30 parts for model training and validation. Then the non-overlapping area of 2017 DEM became the testing area for the study of volume prediction. Geo-environmental variables that influence gully erosion have been derived from the 2017 DEM for both the training area and testing area using ArcGIS and SAGA-GIS terrain analysis modules. Landsat-8 OLI images of 2013 to 2018 (mean reflectance) in the Google Earth Engine (GEE) platform were used for estimating the average land surface temperature (LST) and normalized difference vegetation index (NDVI), a proxy of land cover. Average rainfall for 2012-2015 was derived from CHIRPS (Climate Hazard Group InfraRed Precipitation) climate data in GEE, and road networks were manually digitized in Google Earth (GE).

4.2.1 Selection & evaluation of Study Area

The area taken into measure in this study is a part of the lower Chambal valley (explained in Chapter 2). The main area of interest falls in the Bhind district of Madhya Pradesh, India. Around 4,459 km^2 is the total area of Bhind (Dwivedi & Ramana, 2003), most of which are part of one of the most extensive zones of Indian Badland along the Chambal river. The multi-temporal DEM of the year 2012 and 2017 for the area was taken and processed, then the common area between 2012 and 2017 has been taken for the training and validation model. The uncommon area of 2017 is used as a testing area for the study of gully erosion prediction and volume change assessment. The spatial image of the area is divided into the training area, validation area, and testing area. In figure 4-1. (a) showing the Chambal Ravine Belts of central India, (b) a location map showing the Badland (along the river) under investigation, and the extent of the TanDEM-X digital elevation model (DEM) used in this study. The black box is the 2012 DEM extent, red box is the 2017 DEM extent. Training and Testing areas for gully erosion volume and susceptibility analysis are shown in white dashed boxes. However, the areas other than gullied track covered in the training and testing area (both white boxes) have been masked, it has no value in the final result, only the gully area has been considered in the experiment and result.

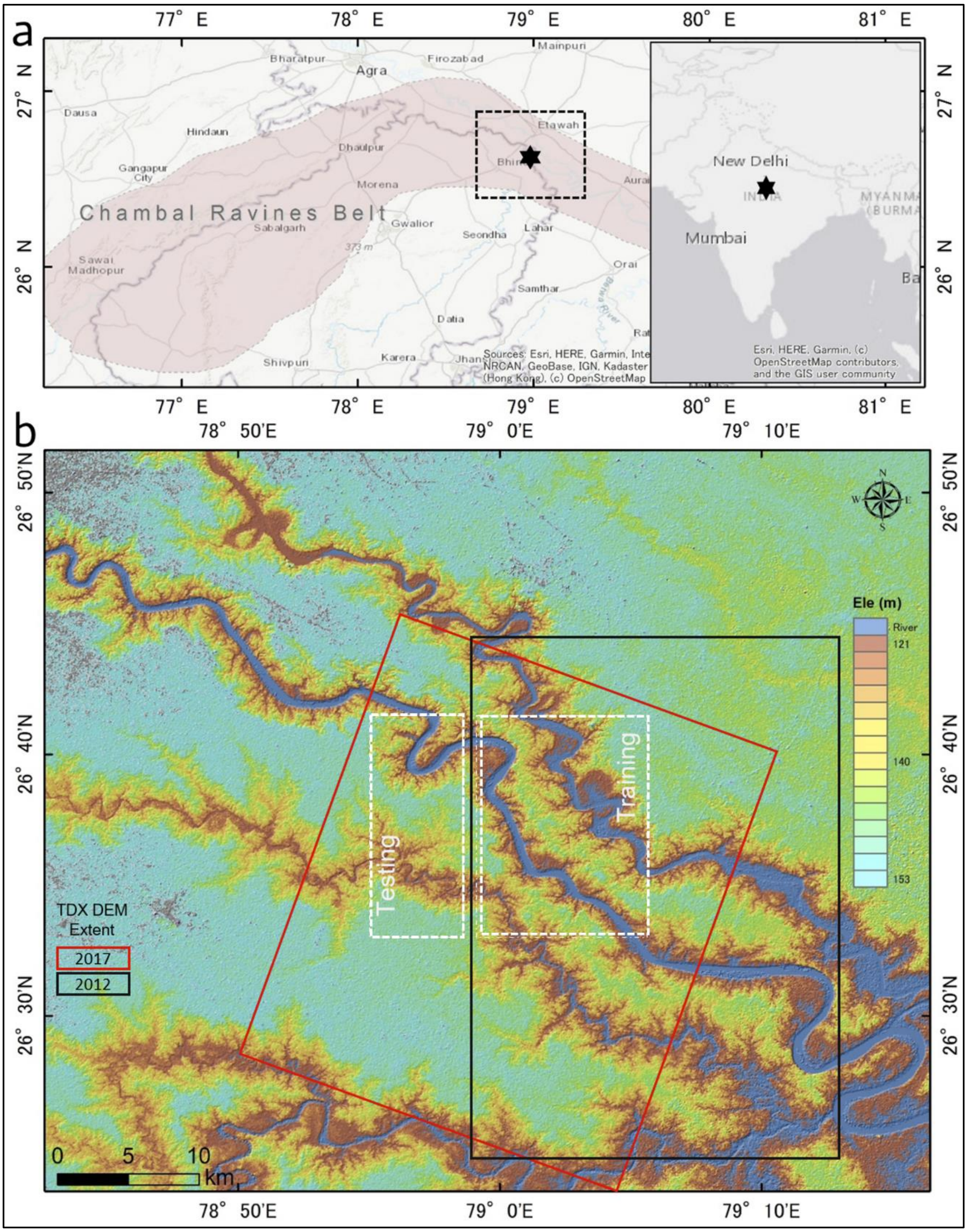


Figure 4-1:(a) showing the Chambal Ravine Belts of central India, (b) location under investigation, and the extent of the TanDEM-X digital elevation model (DEM).

Evaluation of selected Study area:

Further, the selected study area of the Bhind region has been evaluated by comparing it with two more areas for testing the intensity of gully erosion in the other part of the Chambal ravines. The other two sample areas are the region of Dholpur, which is considered as Location-1, and Rajakhera, which is considered Location-2 in this test site. These are also the part of the lower Chambal valley, located beside the Bhind region, situated on the eastern side of Rajasthan state at the border of Madhya Pradesh state. The same procedure has been followed for this evaluation, and multi-temporal TanDEM-X data for the area has been processed. For Dholpur, the data was available for 2012 and 2019 (fig-4-2. a), for Rajakhera the DEM data was available for 2013 and 2018 (fig-4-2. b). All four DEM layer has been processed on ENVI SARscape separately and has been geo-corrected. Then the common area between 2012 and 2019 for location 1 and the common area between 2013 and 2018 for location 2, respectively, has been taken (figure 4-2. (a) (b) black box). The common areas of both locations are the gullied land along the Chambal River (same as Bhind ravine). To compare the intensity of gully erosion between the study area (Bhind) and new locations, the estimation of gully erosion volume has been pursued.

The calculation has been performed on the basis of the DEM subtraction method, on the basis of the DEM difference value between overlapping layers of the common area, the change in volume of the area due to gully erosion has been calculated. The total gully erosion volume in location 1 (Dholpur) is estimated as 76.59 x 10^5 m^3 and the average rate of gully erosion volume is 10.94 x 10^5 m^3/yr (table-4.1.), these numbers are less than the total erosion volume and average erosion volume of the main study area in Bhind region (Section 4.3.1.). Similarly, for location 2, the total gully erosion volume estimated is 126.69 x 10^5 m^3 and the average gully erosion volume is 25.33 x 10^5 m^3/yr (table-4.1.), which is also less than the main study area value. However, the reason for the big difference in values for gully erosion volume change for the new location and study area is possibly due to the difference in the size of the area, therefore the rate of gully erosion volume per hectare per year has been calculated by multiplying the eroded volume (V) by the soil bulk density (1500 kg/m^3) (e.g., Lupker et al., 2012; Sharda & Ojasvi, 2016) and dividing by the time involved (7 years for location-1 and 5 years for location-2) and the area of testing. Following this, the gully erosion rate quantifies for location 1 is 151.83 t ha^{-1} $year^{-1}$ and for location 2 is 165.72 t ha^{-1} $year^{-1}$, value for the gully erosion rate for both the locations is less than the rate of gully erosion in the main study area i.e., 283 t ha^{-1} $year^{-1}$ (Section 4.4.1.). This result shows the intensity of gully erosion is higher in the Bhind region ravine than in the Dholpur and Rajakhera region ravine, though all three areas are part of the same Chambal Badland zone. Hence, the selection of Bhind ravine as the study area is mainly based on the more intense gully erosion hazard in the region.

Table 4.2. shows the estimation of gully deposition volume change value for locations 1 (Dholpur) and 2 (Rajakhera) both. In the comparison, the value of total volume erosion (Table 4.1) corresponds to the value of total volume deposition (table 4.2.) and is similar, for both location 1 and location 2. For example, in location 1, the rate of gully erosion volume change per hectare is $49.05x10^3$ m^3/hr, whereas the rate of gully deposition volume change for this location is 46.12 x 10^3 m^3/ha. The values are remarkably close to each other. Similarly, for location 2, the rate of gully erosion volume and rate of gully deposition volume is also very close i.e., 46.42 x 10^3 m^3/ha and 44.09 x 10^3 m^3/ha, respectively. Comparably, the other values between erosion and deposition are also showing resemblance to each other. This result shows the credibility of generated results from DEM data.

Table 4-1*:* Gully erosion volume change measurement

Gully erosion measurement	**Location 1 (2012-2019, 7 yr)**	**Location 2 (2013-2018, 5 yr)**
Total er. Volume (m^3)	76.59 x 10^5	126.69 x 10^5
Average er. Volume (m^3/yr)	10.94 x 10^5	25.33 x 10^5
Rate of erosion volume (m^3/ha)	49.05 x 10^3	46.42 x 10^3
Average Rate of erosion volume (m^3/yr/ha)	7.01 x 10^3	9.28 x 10^3

Table 4-2: Gully deposition volume change measurement

Gully deposition measurement	**Location 1 (2012-2019, 7 yr)**	**Location 2 (2013-2018, 5 yr)**
Total dep. Volume (m^3)	67.28 x 10^5	110.99 x 10^5
Average dep. Volume (m^3/yr)	9.61 x 10^5	22.19 x 10^5
Rate of deposition volume (m^3/ha)	46.12 x 10^3	44.09 x 10^3
Average Rate of deposition volume (m^3/yr/hr)	6.58 x 10^3	8.81 x 10^3

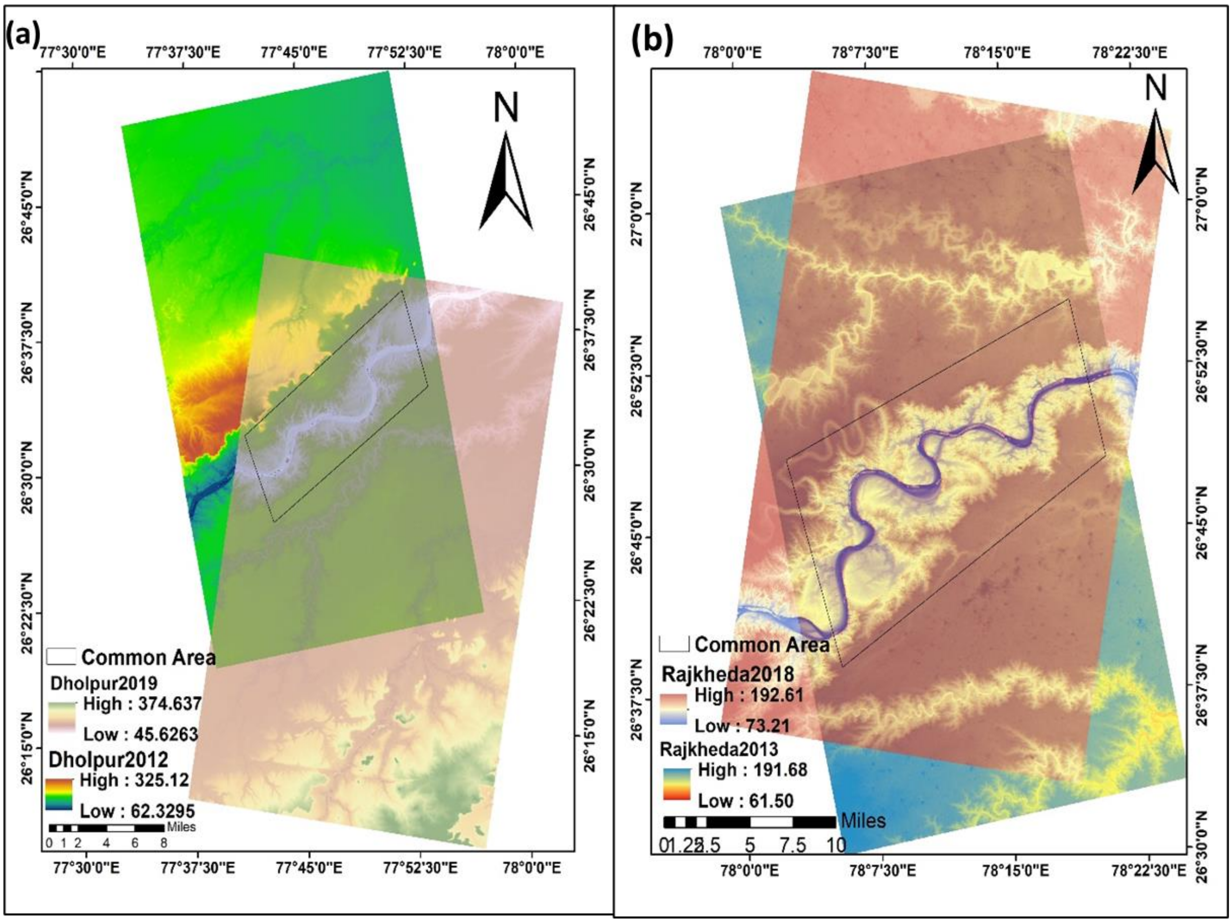


Figure 4-2: Map of sample areas used in the evaluation of the study area. (a) Location1-Dholpur, (b) Location 2- Rajakhera

4.2.2 Factor selection

The selection of geo-environmental variables in gully erosion susceptibility is a crucial step (Conoscenti, Agnesi, et al., 2013). However, there is no consensus or standard methodology that has been set for the selection of different conditioning factors (Merghadi et al., 2020). From the literature, slope gradient, slope aspect, curvature, altitude, lithology, soil texture, distance to streams, topographic wetness index (TWI), distance to road, and land use are the most widely used as gully conditioning factors (Conoscenti, Agnesi, et al., 2013; Gayen et al., 2020a; Lucà et al., 2011; Svoray et al., 2012). Therefore, the following conditioning factors for gully erosion susceptibility and erosion volume prediction (Table 4.3 and figure 4-4). In table 4.3 and figure 4.4 abbreviation is (ELE – Elevation, SLO – Slope, ASP – Aspect, LST – Land surface temperature, CUR – Curvature, SPI – Stream power index, POS – Positive Openness, TRI – Topographic ruggedness index, DAH – Diurnal anisotropic heat, FAC – Flow accumulation, LS – Slope-Length factor, TWI – Topographic wetness index, DTS – Distance to streams, VD – valley Depth, NDVI – Normalized difference vegetation index, LULC – Land use land cover, DTR – Distance to roads, TPI – Topographic position index, RAIN – rainfall, ERO – Volume of Erosion).

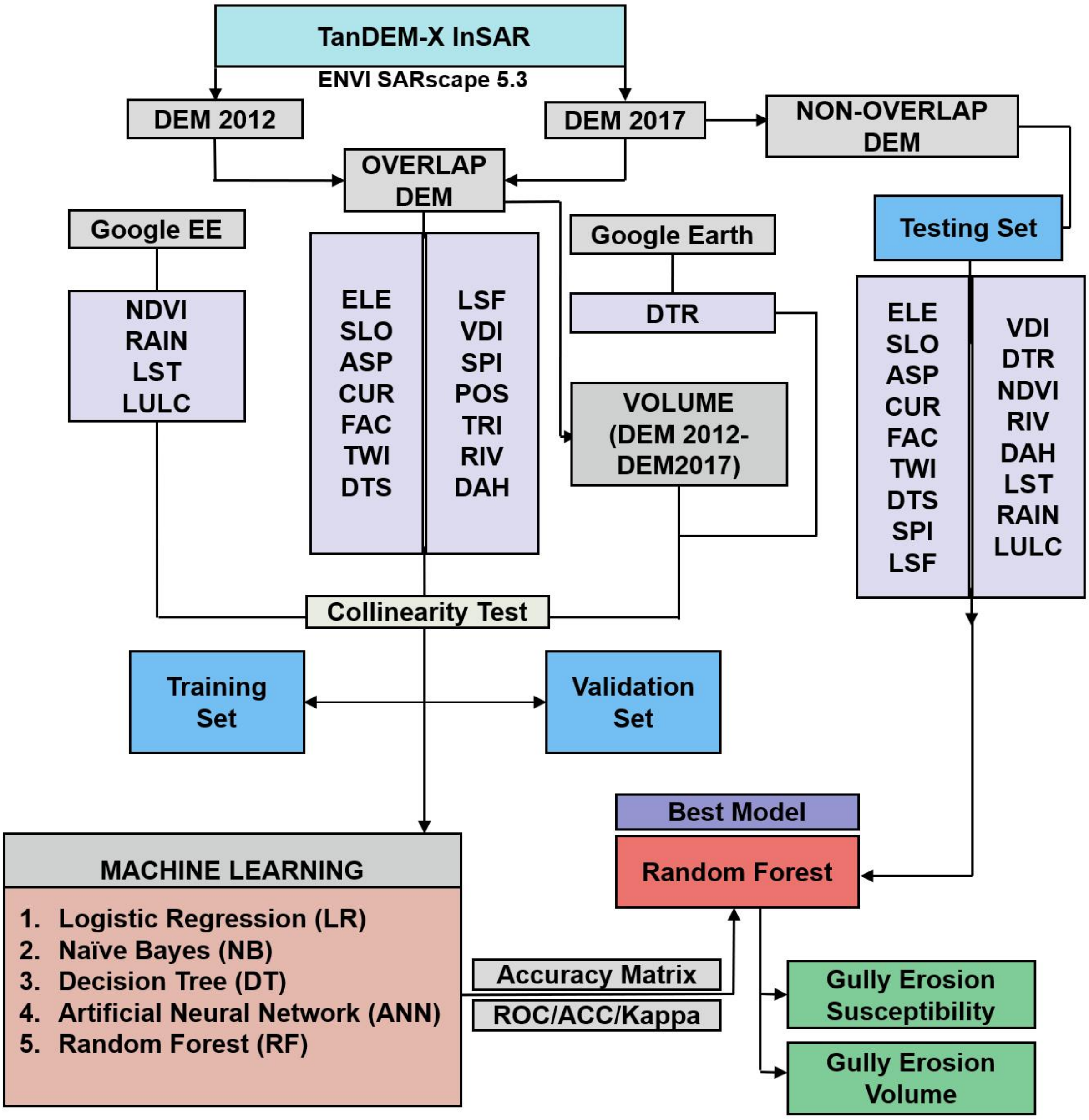


Figure 4-3: Flow chart showing the framework of methods adopted in this work for gully erosion volume prediction and gully erosion susceptibility mapping.

Table 4-3: Conditioning factors used for gully erosion susceptibility and erosion volume prediction.

Elevation	ELE - The elevation data is obtained from Terra-SAR derived digital elevation model prepared at 5 m resolution
Slope	SLO - Slope angle measured in degrees derived from the 5 m DEM in ArcGIS 10.7v.
Aspect	ASP - The Orientation of the slope (North is 0° and 360°, East 90°) derived from the 5 m DEM.
Curvature	CUR - The Curvature function displays the shape or curvature of the slope. It is derived from the 5 m DEM, computed by ArcGIS Spatial Analyst. Planar curvature relates to the convergence and divergence of flow across a surface. A positive value indicates the surface is laterally convex at that cell. A negative plan curvature indicates the surface is laterally concave at that cell. A value of zero indicates the surface is linear.
Positive Openness	POS - Topographic openness expresses the dominance (positive) or enclosure (negative) of a landscape location. Openness has been related to how wide a landscape can be viewed from any position. It has been proven to be a meaningful input for computer-aided geomorphological mapping. POS is derived from the DEM in SAGA GIS (Yokoyama et al., 2002).
Topographic Position Index	TPI - Multi-scale Topographic Position Index, computed by SAGA GIS. This index measures the position of a given DEM cell relative to the ridge and channel with a multi-scale approach where the scaling is proportional to the average size of slopes in a given area. It is calculated based on Guisan et al. (1999).
Slope-Length	SL - Based on the slope and specific catchment area. Extracted from the terrain analysis tool, SAGA.
Flow Accumulation	FAC - Flow accumulation (or contributing area) in m2 relative to each single DEM cell and computed according to the D-infinite algorithm (Tarboton, 1997). Computed by SAGA GIS.

Stream Power Index	SPI - It is the index of the erosive power of flowing water, the calculation is based on slope and contributing area. Derived from hydrological analysis tool of SAGA-GIS.
Topographic Wetness Index	TWI - The measurement of control of topography on the hydrological process acquired from SAGA.
Distance to Streams	DTS - Distance from the channel network extracted using 0.4 km^2 as the threshold contributing area.
Topographic Ruggedness Index	TRI - express the amount of elevation difference between adjacent cells of a DEM, and quantifies the topographic heterogeneity; developed by Riley, et al. (1999).
NDVI	Normalize difference of vegetation index, a proxy of vegetation cover - is derived from Landsat-8 OLI image from Google Earth Engine.
RAIN	The average rainfall parameter between 2012 and 2017 acquired from the CHIRPS dataset, Google Earth Engine (GEE)
LST	The average land surface temperature of area for 2013-2017 is taken from Landsat-8 OLI in GEE.
Distance to Road	DTR - To measure the anthropogenic activity, the road layer of the study area has been manually prepared using Google Earth(GE)
Diurnal anisotropic heat	DAH - Computed by SAGA GIS, measures the average energy input by solar radiation on the ground surface. This tool calculates a rather simple approximation of the anisotropic diurnal heat (Ha) distribution using the formula of Böhner and Antonić (2009) $$Ha = Cos(amax - a) \times \arctan(b)$$
Valley Depth	VD - Valley depth is the vertical distance to a channel network base level: developed by Conrad, (2012).
Land Use Land Cover	LULC – land use land cover map of the study area obtained from the recently released ESRI product. Developed based on Sentinel-2 images.

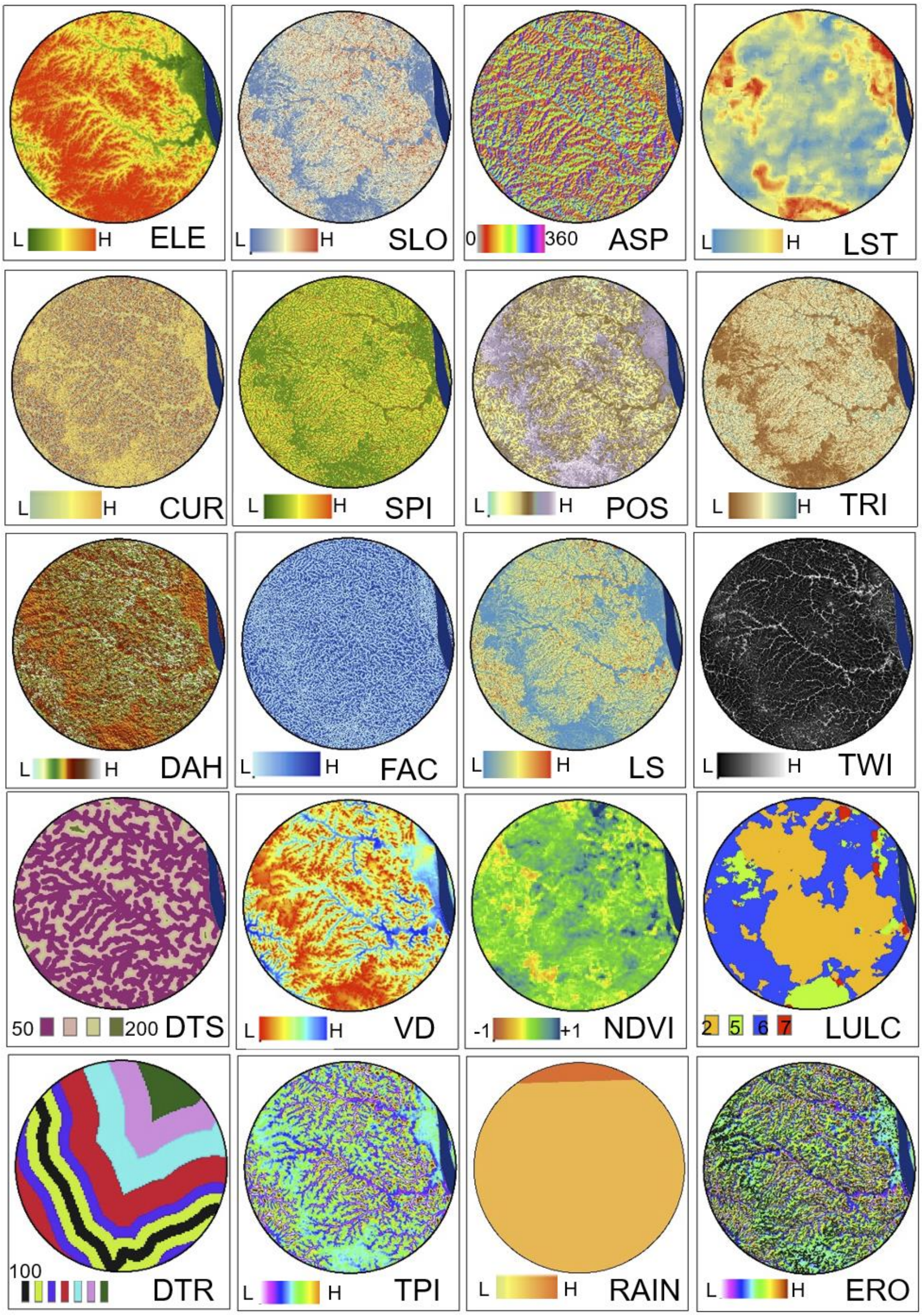


Figure 4-4: Gully erosion conditioning factor derived from digital elevation model, Google Earth Engine, ArcGIS, SAGA GIS, and Google Earth for the study area.

Figure 4-5 demonstrates the multicollinearity result between the variables. Multicollinearity is the occurrence of high intercorrelation among two or more independent variables in the regression model (Merghadi et al., 2020). Removing collinear variables is important because their presence undermines the statistical significance of the results. In this study, the multi-collinearity check has been done with the help of R software packages. Multicollinearity values in statistical analysis are typically represented in the form of a value inflation factor (VIF). According to literature, a VIF >10 stipulate the presence of inter-correlation between variables (Dormann et al., 2013; Merghadi et al., 2018). In our initially selected variables, both TRI (VIF=53.88) and POS (VIF=11.85) show a significant correlation between themselves and with slope variable. Eliminating these two data from the selected factors result in a non-collinear dataset (i.e., VIF< 10) for further modeling work.

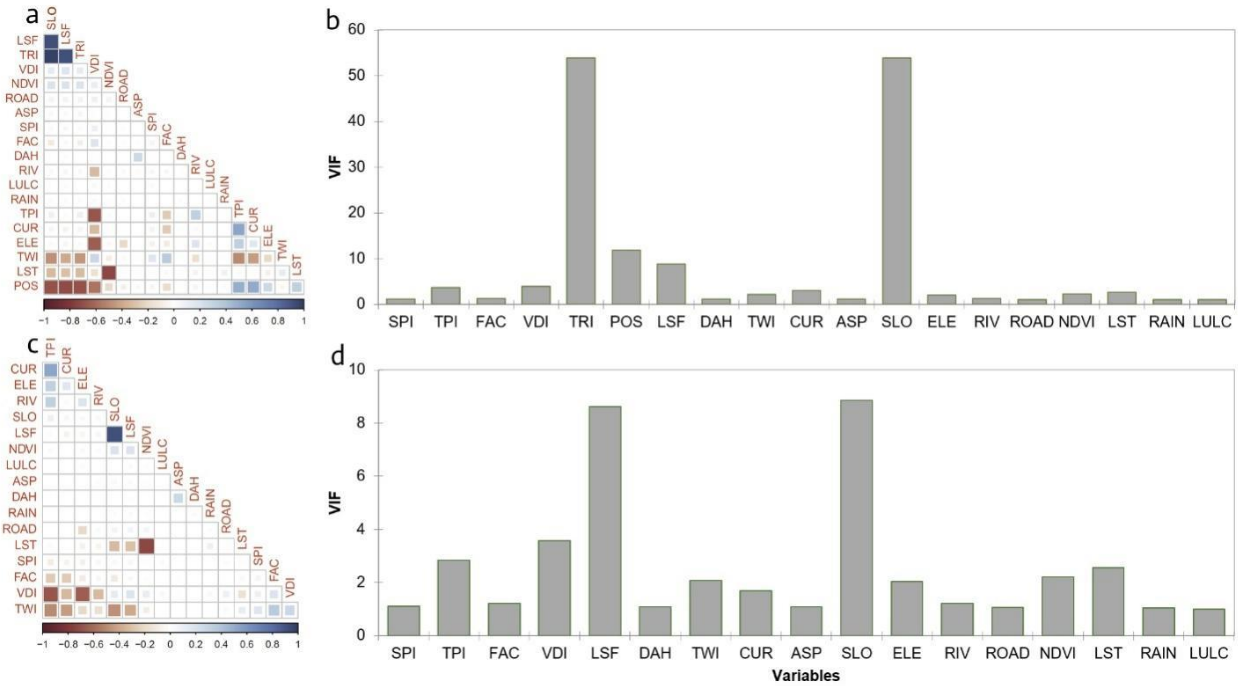


Figure 4-5: Multi-collinearity statistics: a and b show the correlation plot and value inflation factor (VIF) of variables. c and d show the correlation plot and VIF after removing the collinear variables.

4.2.3 Machine learning models

This study employed 5 different machine learning models for gully erosion susceptibility and erosion volume prediction. They are namely: (i) logistic regression, (ii) naïve Bayes, (iii) decision trees, (iv) artificial neural network, and (v) random forest algorithms. These ML models are selected based on their popularity in susceptibility studies (Merghadi et al., 2020), and their ease of implementation in both classification and regression samples. For a detailed description of each ML model and its working principle with examples, readers are referred to Merghadi et al., (2020). In the final stage, Random Forest model was applied to assess the erosion susceptibility and volume estimation selected variables, thereby evaluating changes of predictive power with time. The reason for choosing the random forest in the final stage is that after exploring various machine-learning alternatives (e.g., logistic regression, decision trees, and naïve Bayes and artificial neural network), they were all outperformed by the random forest model (see Section 4.3.2). Also, since our objective is to compare susceptibility estimations made under evolving controls, a statistical inference model was adopted with a low sensitivity toward changes in the independent variable set. RFM is particularly robust in this regard, provided that the forest of binary trees is dense enough (Catani et al., 2013; Dou et al., 2019; Yunus et al., 2019).

A total of 10,000 random samples derived from the conditioning factors and erosion volume were used in machine learning training and another 5,000 independent random samples were used for validation of the models. The hyperparameters used in each ML model, such as tree depth, number of trees, etc., are selected as the default values in the WEKA© environment to replicate the results. For performance evaluation, Kappa values, accuracy (ACC), and the area underneath the receiver operating characteristic (ROC) curve (AUC) were used.

4.3 Results

4.3.1 Gully erosion volume

Figure 4.6 presents the result of the DEM difference (2012 – 2017) derived erosion volume map for the region of interest. It can be seen that gully erosion was prevalent throughout the study area, but it was predominant in the northern and western segments. Quantitative analysis shows that the maximum gully erosion (209×10^5 m^3) was recorded in segment C (north-west) and minimum (60.2×10^5 m^3) in segment G (south-east) (Fig. 4-6. b-c). Figure 4-6 (b) is showing the estimated values of total gully erosion volume in multiple segments in form of a bar graph and Figure 4-6 (c) shows the eroded volume and erosion fill (deposition) volume change for profile x-x'. The average gully erosion volume in the study area was estimated as 135×10^5 m^3 and the total erosion volume was 122×10^6 m^3. The average rate of gully erosion volume between 2012 and 2017 is therefore quantified to be 27×10^5 m^3/y^{-1}. Our study also observed that gully erosion is most prevalent in the slope class of 8º-20º (Fig. 4-6.d.), but the maximum volume density percentage is found in the 16º-20º slope class.

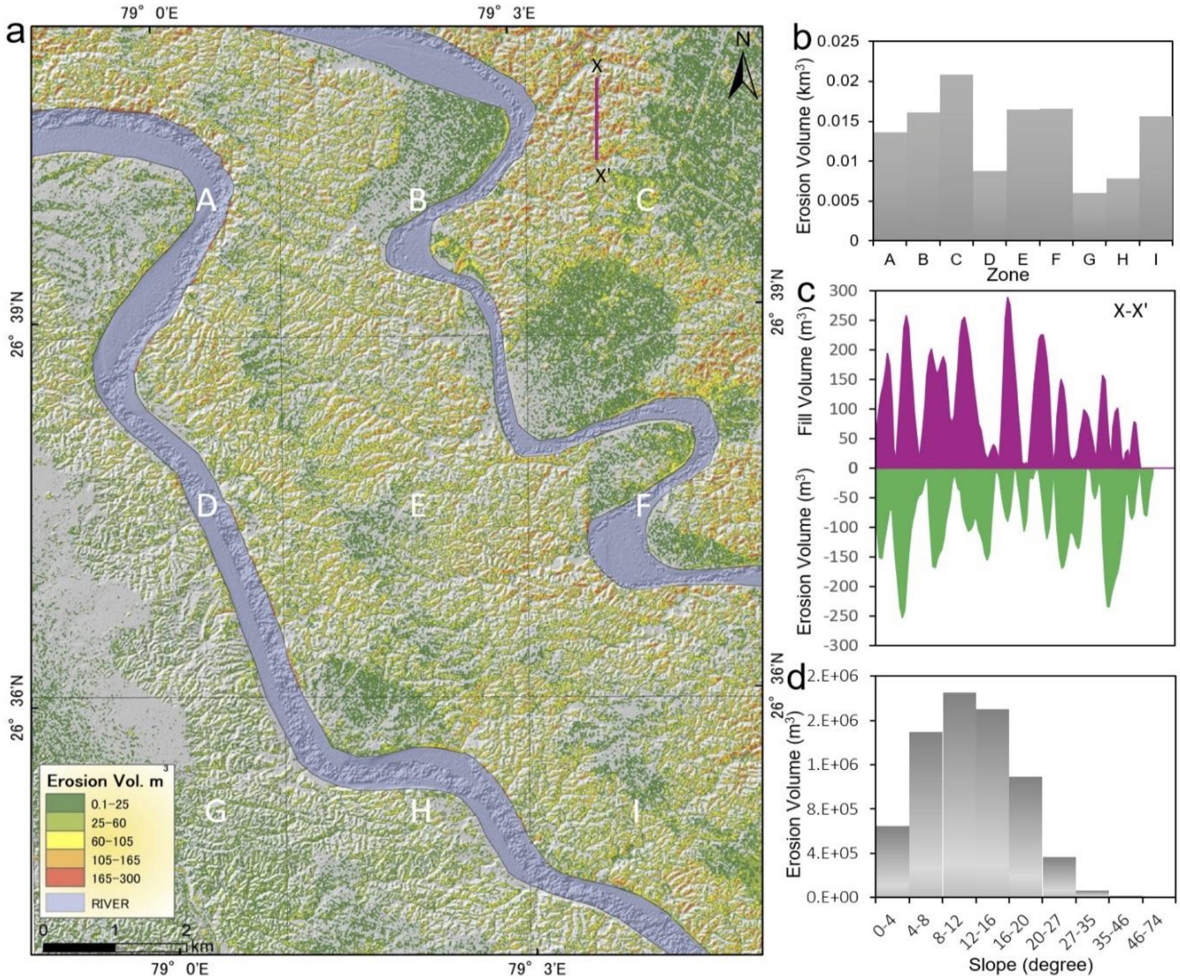


Figure 4-6: (a)Gully erosion volume map, (b) bar graphs showing quantified values of total gully erosion volume in multiple segments. (c) The erosion and fill volume changes for profile x-x' are shown, and (d) shows the slope class of largest (>100 m^3) gully erosion.

4.3.2 Selecting the best fit ML model for prediction

Five machine learning models were employed in this study, namely Logistic Regression (LR), Naïve Bayes (NB), Decision Tree (DT), Artificial Neural Network (ANN), and Random Forest (RF) for the gully erosion volume estimation and gully erosion susceptibility prediction. The performance of these five models was verified by 10000 random sampling pixels extracted from the training site. The result of the goodness of fit is shown in Table 4.4. According to the perceived values, RF has shown an AUC value of 0.85, kappa (0.53), and ACC (77%). The other four models (LR, NB, DT and ANN) came out with overall less efficiency showing values of AUC (0.79, 0.76, 0.67 and 0.82), kappa (0.42, 0.30, 0.35 and 0.50) and ACC (72%, 67%, 67% and 82%) respectively. In statistical learning, an AUC value of 0.5 suggests poor performance (i.e., the ability to distinguish pixels with gully erosion or without gully erosion is low), 0.7 to 0.8 is considered acceptable, 0.8 to 0.9 is considered excellent, and more than 0.9 is considered outstanding (DLong et al., 1988; Mandrekar, 2010). Based on this matrix, the best performing model is RF, and hence they were selected for subsequent susceptibility mapping and gully erosion volume prediction. The ROC plot for all five models is given in figure 4-7.

Table 4-4.: Evaluation matrix of five selected machine learning models using 10000 random sets of training points.

Evaluation Criteria	**Machine Learning Model (Training Set) 10-fold cross-validation**				
	LR	NB	DT	ANN	RF
AUC	0.79	0.76	0.67	0.82	**0.85**
ACC	72%	67%	67%	75%	**77%**
Kappa	0.42	0.30	0.35	0.50	**0.53**

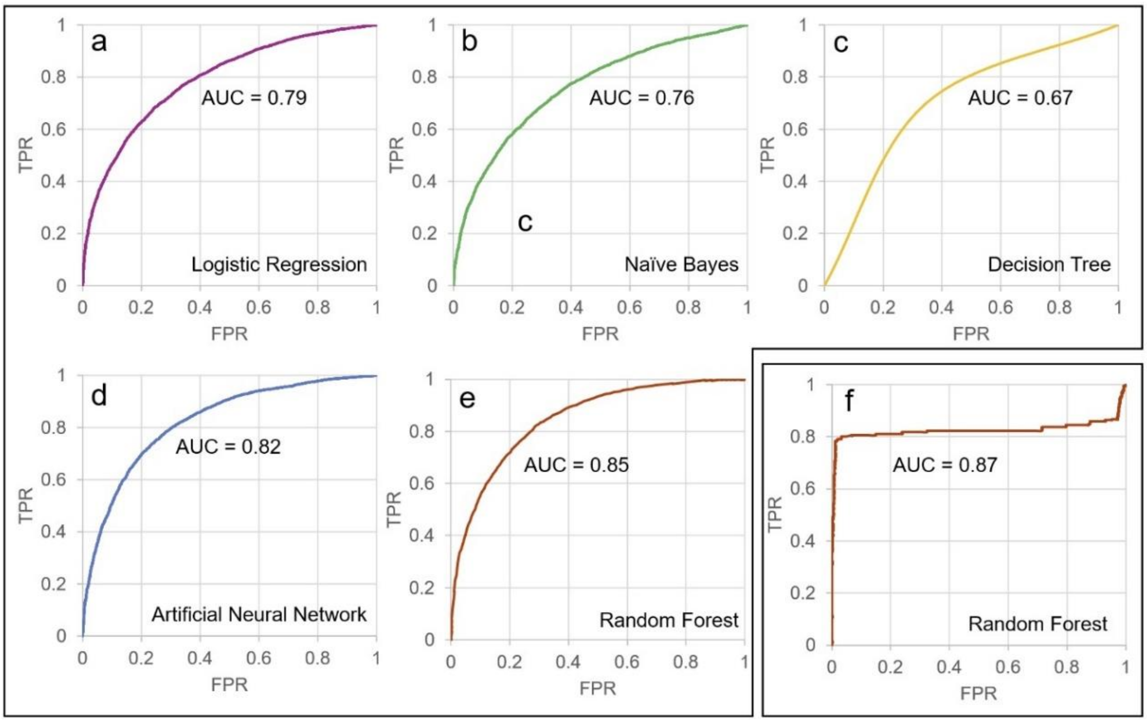


Figure 4-7: The receiver operating function curve (ROC) and area under the curve (AUC) values were obtained for 5 machine learning models (a-e) from training data; and (f) shows the RF based ROC curve and AUC from the validation data.

4.3.3 Gully erosion susceptibility

The susceptibility map for the study area was prepared by applying the RF model using 10000 random pixel information, containing conditioning factors values and location of gully erosion and non-erosion areas as binary (1 and 0) numbers. The gully erosion susceptibility map for the training site is shown in Fig. 4.8a-d. The output map was reclassified based on equal interval method: very low (0.0-0.2), low (0.2-0.4), medium (0.4-0.6), high (0.6-0.8), and very high (0.8-1.0). The efficiency of the mapped model was tested with independent validation data consisting of 5000 random samples (Table 4.5.). The validation accuracy shows an AUC value of 0.87 (also in the ROC plot, figure 4-7.f), indicating the high accuracy of the output maps. However, the susceptibility maps are based on probability (ranging from 0 to 1) of occurrence, thus susceptibility areas were divided into two halves for the ease of calculating the actual areas of gully erosion. The one-to-one correlation between the observed gully erosion areas obtained from the DEM-based subtraction method and those obtained from the RF model (probability >0.5) is shown in figure 4.8b; the coefficient of determination, R^2 value, was found to be 0.89. The total area of observed erosion is 66.12 Km^2 and that obtained from the model is 65.68 km^2.

Since the RF model has shown great potential in mapping areas of active gully erosion, I have also estimated the gully erosion susceptibilities for the testing site (Figure 4-8e). Here, the testing site is the area of a non-overlapping part of the 2017 DEM. Hence validation accuracies are unknown. Nevertheless, the area of active erosion susceptibilities (i.e., probability >0.5) was calculated for the testing site. Out of 131 km^2 areas, approximately 52.67 km^2 areas fell under zones of erosion (probability >0.5). The percentage area of gully erosion in the testing site (40%) is nearly equal to the percent area of gully erosion in the training site (39%); this suggests the superior performance of the output model and its applicability in predicting gully erosion susceptibilities. Our result also shows that the study area is severely affected by gully erosion hazards. Therefore, steps need to be taken in land restoration to arrest erosion and siltation.

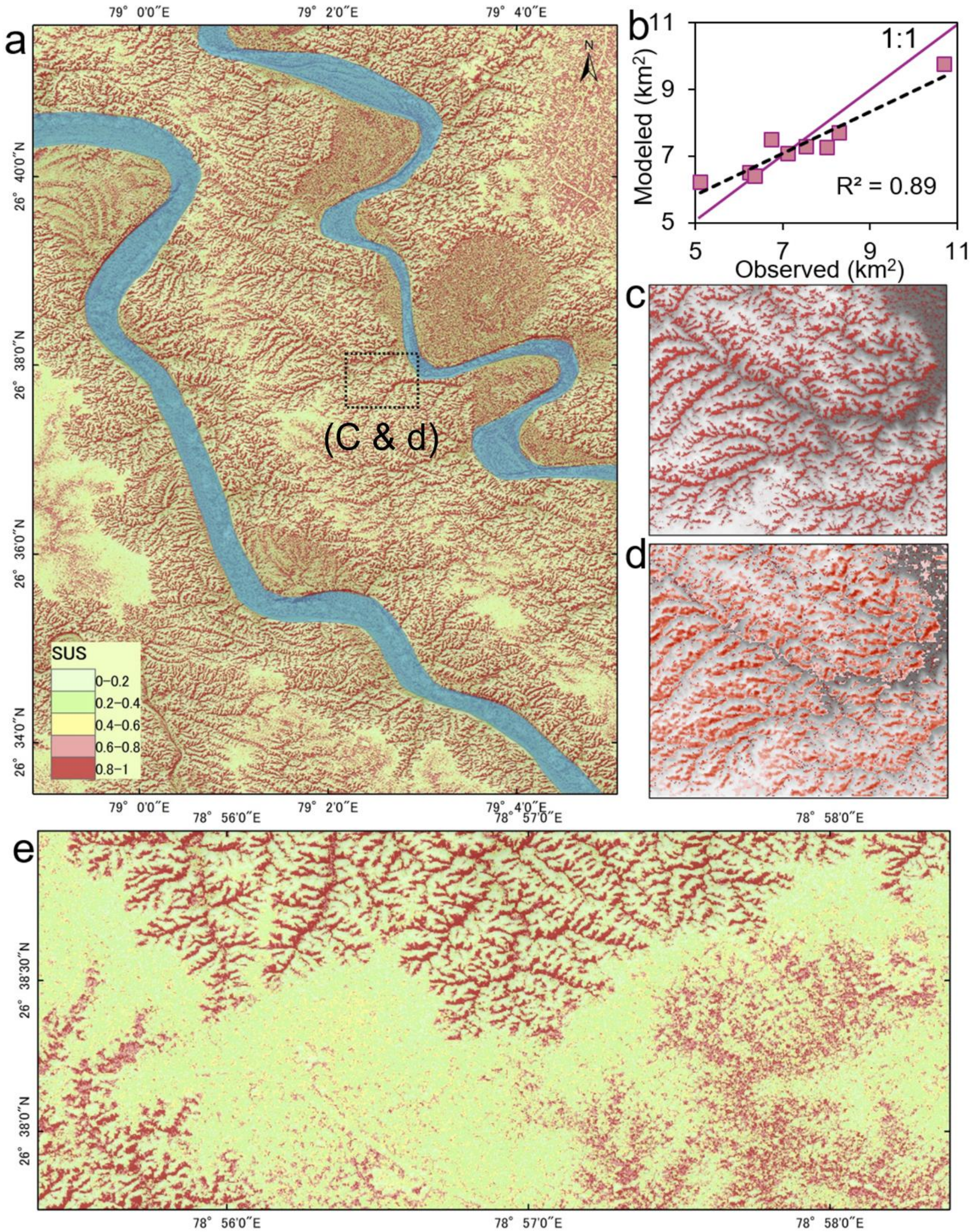


Figure 4-8: Gully erosion susceptibility map for (a) training site, (b) one-to-one correlation between observed gully erosion area (DEM subtraction method) and modeled gully erosion area using RF model for the 9 divisions (see Fig. 5), (c), and (d) are representative site example map showing high-very high gully erosion class obtained from RF model and from DEM subtraction method respectively, and (e) show the gully erosion susceptibility for the testing site.

Table 4-5: Evaluation matrix of the best-fit machine learning model (i.e., Random Forest) for independent validation data (5000 points).

Evaluation Criteria	Best Fit Model (Independent Validation Set)
	RF
AUC	0.87
ACC	97%
Kappa	0.73

4.3.4 Volume change estimation

Because the susceptibility maps present only the location of gully erosion, this information is insufficient to display the areas of active erosion. On the other hand, predicting the gully erosion volume can help us visualize and quantify the potential areas of active erosion, thereby prioritizing the zones for mitigation measures. I predicted the gully erosion volume for the study area based on the same input as given to susceptibility maps. Figure 4.9 presents the gully erosion volume estimation map, showing the erosion volume change in both training (Figure 4-9a) and testing area (Figure 4-9c).

The uncertainties in volume prediction were estimated based on the observed volume and modeled volume in the training area (Figure 4-10). The correlation coefficient (r) and mean absolute error (MAE) for the predicted gully erosion and fill volume are 0.79 and 35.59, respectively. Although the predicted output underestimated the volume in the erosion and fill category, the generation of such volume maps is greatly helpful for visualizing the areas of active erosion. Moreover, the accuracy of the volume prediction can further improve with additional input data and hyperparameter tuning.

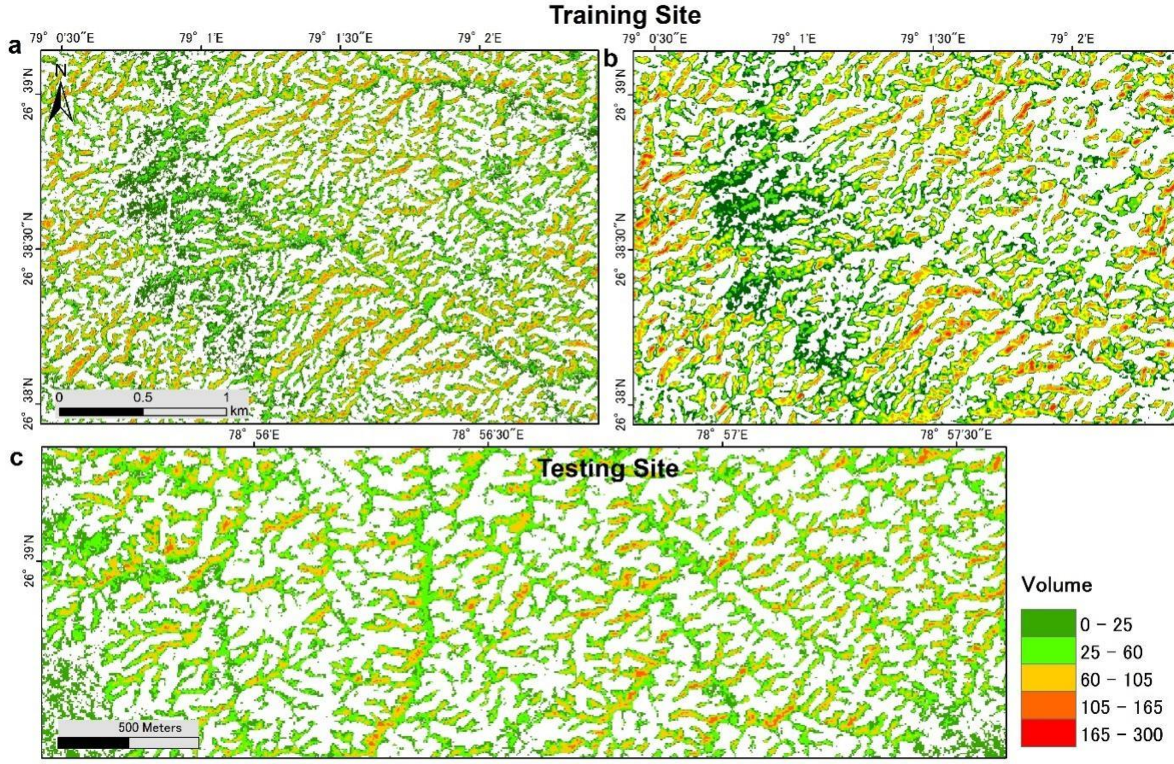


Figure 4-9: Gully erosion volume (m^3) predicted (a) for the training site and (c) testing site. (b) shows the observed erosion volume in the training site obtained from the DEM subtraction method.

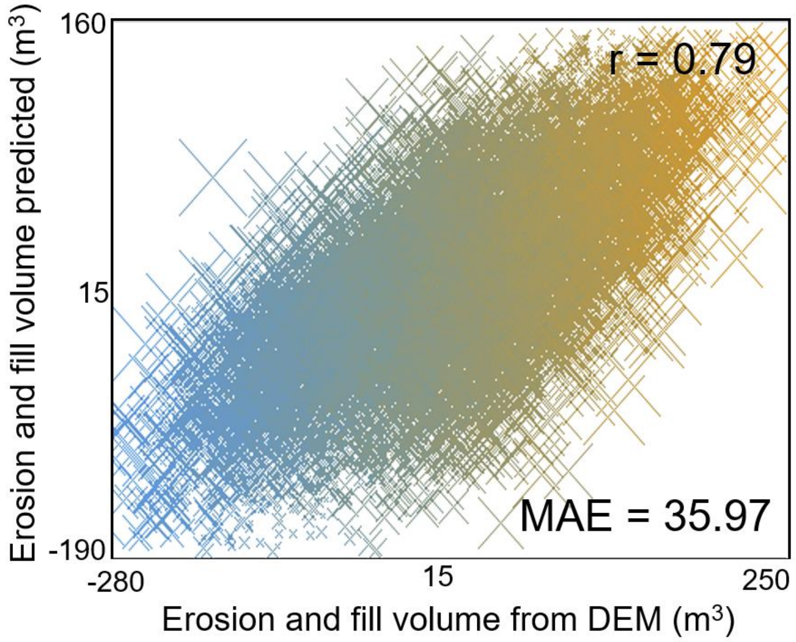


Figure 4-10: Visualizing gully erosion volume prediction and error estimation (MAE = mean absolute error; r = correlation coefficient) based on the RF model.

4.4 Discussion

4.4.1 Soil erosion rate of Chambal Badland

Gully erosion is recognized as one of the most serious environmental issues in the Chambal valley of Central India. However, unfortunately not a clear understanding of the gully erosion rate on Chambal Badland changes was reported. Several studies have attributed anthropogenically driven activities as the main factor of gully land changes and erosion. Using satellite images between 1971 and 2015, Marzolff & Pani (2018) mapped the Badlands in Lower Chambal Valley and noted that most of the area underwent human-induced reclamation and converted Badlands into agricultural land. They found that nearly 23% of Badlands in the study area have been leveled over the period of 45 years. But the anthropogenic activity in the region is not homogenous and hence the gully erosion levels as well. Nevertheless, the gully leveling rate is found to be increased, up to 10 times in recent years compared to the 1970s (Marzolff & Pani, 2018) The rise in population, using heavy machinery for random and quick land leveling, and the construction of check dams in the valley bottoms are the major causes of a recent increase in erosional activities (Pani 2016; 2017; Ranga et al., 2016).

While areal changes have been reported based on field observations and high-resolution satellite images, most of the volume change estimates or erosional rates of Chambal Badlands are made from the empirical method by using the Revised Universal Soil Loss Equation (RUSLE). For instance, Suryawanshi et al., (2021) estimated the soil erosion rate of 11 river basins of Madhya Pradesh, including Chambal, and reported a value of 6.12 t ha^{-1} year^{-1} as the average soil erosion rate in the state. The estimated values for the Chambal basin were found lower than the state average (3.04 t ha^{-1} year^{-1}). Kumar et al., (2020), reported 32.08 t ha^{-1} year^{-1} as the mean soil erosion rate in the gullied areas of the Parbati sub-basin, a tributary of Chambal. A few other works even reported much larger erosion rates; for example, Khan & Govil, (2020) studies show about 445 t ha^{-1} year^{-1} erosion in the Yamuna flood plain region. The large differences in erosion rates between these studies might arise from (i) study area differences, (ii) the selection of input DEM, and (iii) from the selection of coefficients used in the formula (e.g., α and β in C-factor). Additionally, it was noted that RUSLE mainly accounts for soil loss via sheet and rill erosion and ignores the effects of gully erosion (Rowlands, 2019). Furthermore, RUSLE does not have the capability for routing sediment and hence cannot account for sediment deposition (Ganasri & Ramesh, 2016). Because of these constraints, RUSLE is at best a coarse predictor of soil erosion rates.

The average soil erosion volume calculated from DEM-based estimates in our study is 135×10^5 m^3. These values are closer to the one reported by Gosh et al. (2018) for the Daulatpur section of Ganga ravines marginal planes (i.e., 130×10^5 m^3). Accordingly, the soil erosion rate is calculated by multiplying the eroded volume (V) by the soil bulk density (1500 kg/m^3) (e.g., Lupker et al., 2012; Sharda & Ojasvi, 2016) and dividing by the time involved and area of interest (143 km^2) is approximately 283 t ha^{-1} $year^{-1}$. Although the calculated value is significantly larger than that reported in Kumar et al., (2020) and Suryawanshi et al., (2021), but their studies accounted non-ravenous portion of the basins as well, which may have resulted in the lower erosion estimates. Nonetheless, it should be noted that the study area is part of the most extreme form of the Chambal ravine, and the Chambal river has found a sediment load of 220×10^5 tons per year (Ranga et al., 2016); validating our initial findings. Further analysis on catchment level monitoring is recommended for future works.

4.4.2 Factors controlling gully erosion

The information gain (IG) function that evaluates the worth of an attribute by measuring the most information present within all the attributes concerning the dependent class has been used as a popular machine learning technique to identify the significant controlling factors that contribute to the prediction of class variable (Merghadi et al., 2020; Yunus et al., 2021). Accordingly, the IG was applied to this study: as per the resultant IG ranking, the most contributing conditioning factors for the gully erosion are aspect, topographic position, topographic wetness, and curvature (Figure 4-11). Flow accumulation, valley depth, stream power, and diurnal anisotropic heat followed these scores. Factors such as NDVI, LULC, LST, distance to channel and roads do not contribute much to the prediction.

The IG results suggest that the second-order derivative of DEMs with high-resolution inputs is more important in susceptibility studies of smaller features such as gullies. On the other hand, factors such as LULC, NDVI, LST, and road layers are sourced from different datasets, and their original resolution may be insufficient for predicting gully erosion. Moreover, the region's vegetation (NDVI is used as a proxy) and land use (LULC) are mostly homogenous. One another possible reason for their least score in IG may be attributed to this phenomenon.

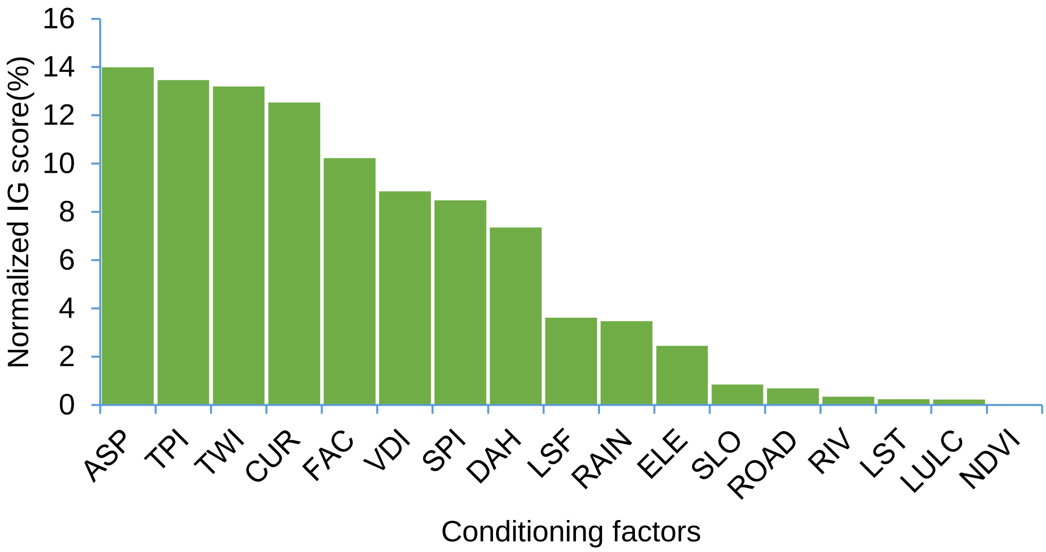


Figure 4-11: Information gain scores (normalized) were obtained for the different gully erosion conditioning factors

4.4.3 Significance of the study

The study area considered here is the most extensive zone of Badland in India. The environmental and socio-economic condition of the area is at high risk of degradation in terms of natural resources and human life quality (Pani, 2016). The people's livelihood in these localities depends on agriculture as the primary income source. Recently, the government and local community and even at the individual level, residents of the area are effectively involved in restoring the gully erosion and ravines reclamation. Despite this, there is not any methodological design for gully erosion susceptibility assessment in this area with the gully erosion effect. In this study, apart from the gully erosion susceptibility map, an attempt has been taken to estimate the change in gully erosion volume.

The finding identified not only the areas of gully erosion but also detailed the active zones of erosion; this will help authorities prioritize the land restoration and reclamation action plans. The following gully erosion mitigation measures were recommended previously and practiced in the Chambal valley, such as contour farming that involves planting rows of crops, strip cropping i.e., planting alternative strips of crops and grass parallel to the contours, terracing, and construction of check dams (Pani, 2016). Our IG analysis indicates that aspect and topographic position are the major controls of erosion susceptibilities in the region. The effect of the slope aspect in determining soil moisture and solar radiation and associated vegetation dynamics is a well-known phenomenon (Kong et al., 2019; Zhang et al., 2020). Henceforth, I further recommend additional practices such as planting vegetation in slope aspects deprived of vegetation. Identifying the erosion severity maximum zones in our study also helps narrow down check dam constructions areas. The framework presented in this research using machine learning techniques can also be applied to other areas of Chambal and have the potential to play a key role in monitoring and management, especially in inaccessible ravines.

4.5 Conclusion

Monitoring morphological changes occurring in Chambal Badland by using a more efficient and accurate technique like multi-temporal DEM mapping and machine learning techniques is essential for ravines mapping in the restoration and reclamation process. This research contributes to a systematic prediction of gully erosion susceptibility and evaluation of volume change by using an integrated framework of remote sensing, GIS, and random forest modeling. Our study came up with significant results, concluded as follows:

- The Random Forest model is approved as the best model with the highest accuracy in terms of ROC-AUC value for gully erosion susceptibility mapping when compared with logistic regression, naïve Bayes, decision tree, and artificial neural network.
- The model transferability (i.e., the ability of the model to perform in other regions) for gully erosion susceptibility assessment to other regions is also found valid.
- The gullies of the Bhind areas-ravine (part of lower Chambal valley) in Central India showed that the area is highly prone to soil erosion. The average soil erosion volume is 135×10^{5} m^{3}, and the average soil erosion rate is ~283 t ha^{-1} yr^{-1}.
- The current study successfully predicted the change in volume of the selected area due to gully erosion with a correlation coefficient of 0.79 and a mean absolute error of 35.97. Especially the north-northeast location is severely affected by gully erosion, whereas the south-west part of the area shows less volume change by the gully erosion process.
- The methodology and outcome of the current research are helpful in land degradation assessment and ravines reclamation in India. It can also be utilized for environmental monitoring and management in ravine reclamation programs, land use planning, and infrastructure development. Furthermore, it can be useful for developing appropriate soil and water management practices in ravine-affected rural areas.

Chapter 5: Evaluating the effect of DEM from a different source in Gully erosion susceptibility mapping

5.1 Introduction

Land is the major contributor to Life, Bio-diversity, and the human community, it supports the vital life-sustaining system (Keesstra et al., 2018; Razavi-Termeh et al., 2020). Therefore, land degradation is one of the most concerning issues in the national and international agenda (R. Kumar et al., 2021). Land erosion by water is the most dominant plus dynamic natural phenomenon and a severe environmental problem, often resulting in gully erosion and ravines formation, the most degraded landform. Gully formation is a soil erosion process, the concentrated flow of water accumulates and forms a narrow channel that is further converted into a deep channel after removing the parent soil material (Arabameri, Pradhan, et al., 2018; Kariminejad et al., 2019; Kirkby & Bracken, 2009; Poesen et al., 2003; Pourghasemi et al., 2020); And the several of gullies network forms Ravine in the final stage. It is a highly unproductive and vulnerable land type also known as Badland in some countries (Chaturvedi et al., 2014) and mainly occurs in arid or semi-arid regions (Azareh et al., 2019; Bernini et al., 2021).

Gully and ravine formation is a natural process but often accelerated by anthropogenic activities such as Forest cutting, incorrect agriculture practices, inappropriate land use, clearing of vegetation, etc. (Azareh et al., 2019; Ionita et al., 2015; Rodrigo Comino et al., 2015). It creates huge ecological and social destruction such as- it cause flooding, desertification plus sedimentation in the water body (Arabameri, Pradhan, et al., 2018; Mojaddadi et al., 2008; X. Zhang et al., 2018), restricts the use of land in agriculture by damaging the fertility of the soil (Arabameri, Pradhan, et al., 2018; Derose et al., 1998; Rahmati et al., 2017a); on the other hand, it cause huge economic loss to the rural and urban area by damaging the infrastructure and transportation (Odunuga et al., 2018; Zabihi et al., 2018). The socio-economic status of the people living in ravines is very retarded, and usually, the population is below the poverty line (Pani, 2016, 2018, 2020b). Around 10 million hectares (almost one-third) of the world's cultivated land, including India, are affected by erosion annually (Derose et al., 1998; Sun et al., 2014). Ignorance of gully erosion can be turned into a disaster in the future and hence it should be effectively considered in policymaking for land restoration and management programs. Sustainable Development Goal (SDG) 15 advocate for "Life on Land" which declare to combat desertification, restore degraded land and soil, drought, and floods, and strive to achieve a land degradation–neutral world' by 2030. It has been endorsed in the 2030 Agenda of Land Degradation Neutrality program by UNCCD, 2012.

Gully erosion susceptibility mapping (GESM) of the area is a very crucial part of any land restoration project. The accurate gully erosion susceptibility needs high-quality data with precise information and advanced tools and technology. In this respect, remote sensing and GIS play very significant roles in providing and handling a variety of spatial data, faster data processing capacity, and easy analysis (Avtar et al., 2019; Chang et al., 2019; Dou et al., 2019). For several years GIS has been used in gully erosion as well as in many fields (Avtar et al., 2020; Bocco et al., 1990; Conoscenti, Agnesi, et al., 2013). In recent decades, along with GIS, Machine learning has been used widely and efficiently in many studies targeting accurate gully erosion estimation and assessment (Al-Abadi & Al-Ali, 2018; Arabameri, Asadi Nalivan, et al., 2020; Arabameri, Pradhan, et al., 2018; Gayen et al., 2020b; Pourghasemi et al., 2020; Rahmati et al., 2017b). The studies approached machine learning in generating GESM, compared and highly recommended Random Forest (RF) model as one of the most accurate and robust models (Avand et al., 2019; Gayen et al., 2020b; Hosseinalizadeh et al., 2019; Raj et al., 2022).

The global Digital Elevation Model (DEM) is an essential element in the GIS-based study of gully erosion to obtain the topographical information of the area as the erosion process is highly affected by topographic attributes (Grohmann, 2018). The accurate topographic input is an important part of GES mapping. Previous studies suggest that the topographic variables derived from the traditional method or other methods like morphometric analysis of cartographic representation are not very accurate in lower resolution (Chowdhuri et al., 2021; Legorreta Paulin et al., 2010). Digital Elevation Model (DEM) is found to be more popular and has been widely used to provide accurate topographical features with precise attribute information (Garosi et al., 2018). DEM yield and supplies most of the essential gully affecting factors, environmental variables, hydrological features, and land use information. The properties of these variables alter with changes in DEM resolution (J. X. Zhang et al., 2008). But, there is still a lack of clearance regarding the most suitable and optimal resolution of DEM (pixel size) of DEM in the erosion prediction process (Garosi et al., 2018). Most of the studies focus on the production of more effective GESM where the DEM quality from different sources and its resolution factor effect was not discussed (Kheir et al., 2007). In addition, recently there are many new advantages have been evolving in DEM technology which can affect the result of erosion analysis significantly. Especially the quality of DEM data affects the research based on machine learning exceptionally, it proves that the selection of a suitable DEM and its optimal resolution can lead to a very successful gully erosion study.

In this respect, the present study focuses on analyzing the effect of DEM from a different source with various resolutions on Random Forest model accuracy for gully erosion susceptibility mapping in Chambal Ravines of India. In India, ravines have affected 3.97 million hectares of cultivated land, of which Chambal ravines cover 2.7 million hectares almost 70% (Upadhyay & Chauhan, 2019). Yamuna-Chambal ravine zone is the largest Badland in India, border the river Yamuna and Chambal, and occurs in many states. The study has considered the lower part of Chambal Ravines, which fall in the Bhind region of Madhya Pradesh (central India). The area consists of a complex network of deep gullies, steep ridges, and low hills (Pani, 2016). Population in the area is mainly dependent on agriculture for livelihood and living below the poverty line, (Pani, 2018). The area is in continuous consideration for reclamation and restoration projects by state, national and international governments as well as showing positive results (Pani, 2020b). This land can be productively utilized in the economic upliftment of ravines dwellers by making policies to minimize human-induced factors, correct agriculture practices, suitable plus sustainable land use, and land reclamation program.

5.2 Methods and Materials

5.2.1 Selection of Study Area

The study area is Bhind, situated in Madhya Pradesh state of central India. It represents the Chambal ravines, one of the most extensive Badland in the world. The total area of Bhind is 4,459 km^2, which is situated at 26°69’71’’N to 26°15’17’’N latitude and 78°62’08” E to 78°61’94” E longitude (Dwivedi & Ramana, 2003). The six DEMs from different sources and of different resolutions have been acquired for the selected study area (figure 5-1).

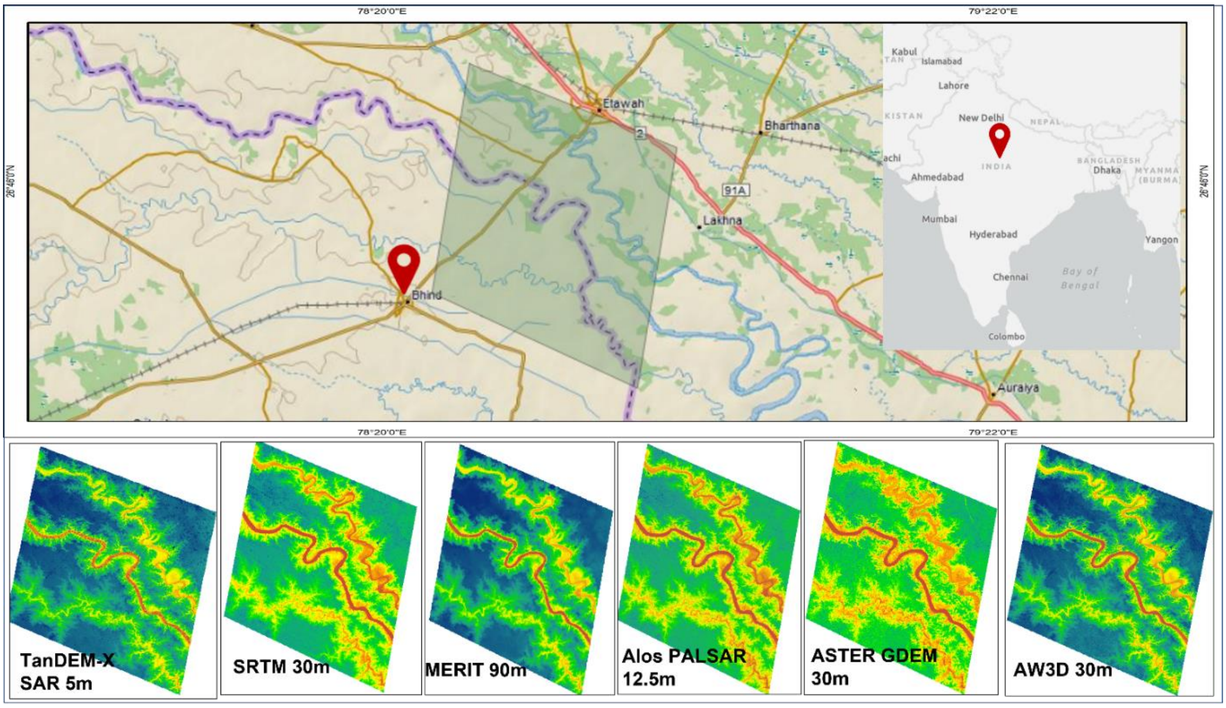


Figure 5-1: Study area, the part of Chambal ravine in Bhind region of central India. The green box in the location map is the region under investigation and is used to derive the six different DEMs for this study.

5.2.2 Framework of Methodology

The study has focused on developing the understanding of suitable DEM selection in Gully erosion susceptibility mapping by machine learning model. For this purpose, six different types of DEMs and the Random Forest machine learning model have been addressed to evaluate the efficiency of the production of accurate gully erosion susceptibility. To predict the DEM resolution effect in gully erosion monitoring, the plot of the lower Chambal ravine area from Bhind district has been selected. One part of this methodology is the data extraction and data process the other part is comprised of data Simulation (Figure 5-2 and 5-3, respectively).

5.2.3 Data Extraction

There are six DEMs with different resolutions and data quality that have been approached in this study i.e., SRTM with 3om, ALOS PALSAR with 12.5M, MERIT with 90m, ASTER GDEM with 30m, AW3D with 30m, and TanDEM-X with 5m. SRTM and ASTER GDEM were derived from USGS Earth Explorer. MERIT and AW3D were processed from Google Earth Engine (GEE) and ALOS PALSAR was extracted with the help of the Alaska Satellite Facility (ASF). The TanDEM-X multi-temporal DEM was acquired by the German Aerospace Center (DLR) and processed by employing the ENVI SARscape. The horizontal and vertical geo-correction had also been done for the DEMs before proceeding. Later on, all the gully controlling factor applied in the study was procured from all the six DEM separately with the help of ArcGIS and SAGA GIS and the environmental variables were obtained with the help of Google Earth Engine (GEE) and Google Earth (GE). NDVI (Normalized Difference Vegetation Index) and Average Land Surface Temperature (LST) derived from Landsat-8 OLI image of Google Earth Engine (GEE). The CHIRP climate data of GEE was used to obtain the average Rainfall for the area. Whereas the Distance from Road was digitized from Google Earth (GE). Figure 5-2 shows a flowchart of the data extraction process in this evaluation. These are the gully affecting factors considered in this study and the abbreviation for gully affecting factors used in the figure are- DEM – Elevation, SLO – Slope, ASP – Aspect, LST – Land surface temperature, G_CUR – General Curvature, L_CUR– Longitudinal Curvature, Pla_C– Plan Curvature, CAT_A– Catchment Area, CAT_S– Catchment Slope, M_CAT– Modified Catchment Area, SPI – Stream power index, POS – Positive Openness, TRI – Topographic ruggedness index, FLAC – Flow accumulation, LS – Slope-Length factor, TWI – Topographic wetness index, NDVI-Normalized difference vegetation index, LULC – Land use land cover, DTR – Distance to roads, TPI – Topographic position index, RAIN – rainfall).

Volume Map preparation- For the gully erosion volume calculation, two overlappings DEMs of TanDEM-X for 2012 and 2017 were taken and subtracted. With the help of raster calculation in ArcMap, the volume of every pixel fall in the overlapping DEM area is calculated by the DEM subtraction method.

5.2.4 Data Simulation

After the selection and extraction of all six DEMs with the gullying factors, the following procedure has proceeded in order to meet the objective (Figure 5-3).

- The gully affecting factors is derived for each DEM one by one with the help of GIS, Google Earth Engine, Google Earth, and SAGA.
- The value of volume change caused by gully erosion in the area has been taken from the subtraction of two overlapping TanDEM-X DEM of 2012 and 2017 of the study area.
- 25000 random points have been taken from each DEM separately, to see the difference in point value in all the five DEMs. These random points are the same for all the DEM. The most favorable number of random points was selected after testing with several sets of points number.

- The value of 25,000 random point for all the gully affecting factors for all the 6 DEM has been extracted separately with the help of ArcMap.
- In this way, with the value of random points for all the factors and volume of the area, the training model has been prepared for all six DEMs separately.
- The training model has been tested on random forest machine learning. Each training data set gave a different ROC/AUC value on the random forest model, which determined the accuracy of the model affected by the DEM with various resolutions.
- Then the gully erosion susceptibility maps were built from the training model by all DEMs.
- GESM by TanDEM-X has been constructed for the whole study area. The area was divided into nine parts and modeled to generate the map.
- And the GESM prepared from the other five DEMs is based on the point location of erosion, to predict the pixel point value difference between the GESMs for erosion susceptibility.

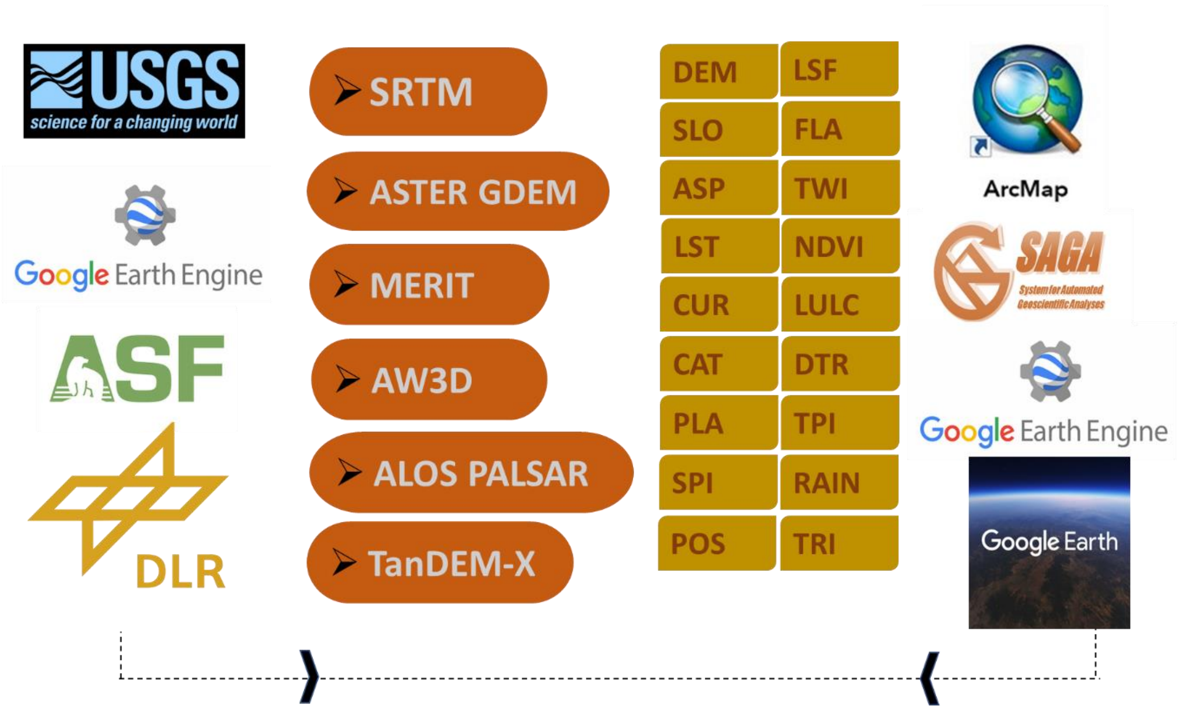


Figure 5-2: Flowchart of Data extraction, applied in this study for DEM evaluation and gully erosion susceptibility mapping.

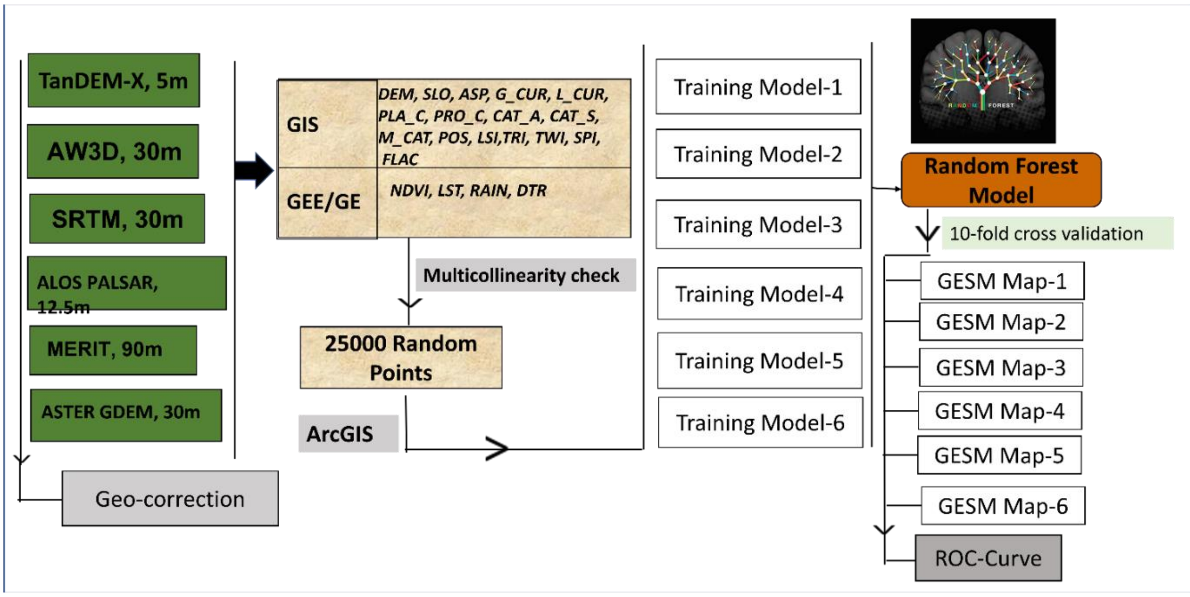


Figure 5-3: Flowchart showing the methodological framework applied in this Research for Gully erosion Susceptibility mapping.

5.2.5 Database Used

The study has been carried out on five different DEMs, their resolution, and data sets. SRTM and ASTER GEDM with 30m spatial resolution were derived from USGS; MERIT with 90m resolution and AW3D with 30m resolution were processed with the help of Google Earth Engine; ALOS PALSAR with the highest 12.5m resolution was derived from ASF (Alaska satellite facility) for the year 2017. The area also went through geo-correction to check the horizontal and vertical displacement. Further, the geo-morphological and hydrological features were further derived from each DEM sample area using ArcGIS and SAGA-GIS. Then after a multi-collinearity check, 18 features from all these have been chosen for gully affecting factors input for calibration (training model). The 25,000 random points were taken from each six DEM; the number of random points is the same (Figure 5-4), which means the pixel points taken to extract the topographic value is the same, but the pixel value will-differ because of different DEM resolution and source. And values of gullying factors, including the value of volume difference, were extracted for these 25,000 random points. The value of volume change was derived from the subtraction of DEM of 2012 and 2017.

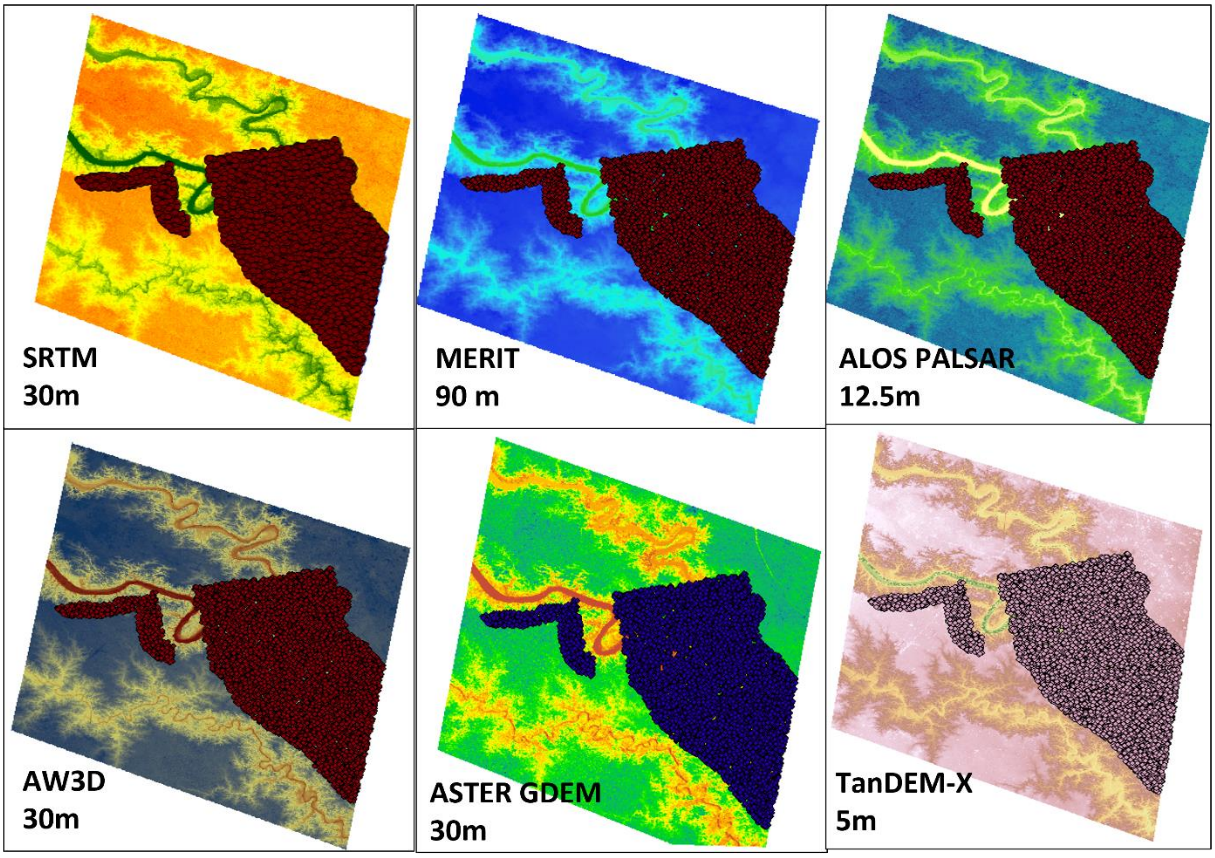


Figure 5-4: Location of the pixel points taken in this study to extract the topographic value.

5.2.6 Selection of DEM

A Digital Elevation Model is a representation of elevation data used to illustrate the terrain surface in a 3D computer graphics form. DEM quality is defined by the accuracy of elevation at every pixel (Szypuła, 2019). Among several factors, the DEM resolution also determines the quality of a DEM. Recently it has been used widely in terrain parameter analysis. In this study, six different types of DEMs have been considered to examine and compare the accuracy of gully erosion susceptibility i.e., SRTM, ALOS PALSAR, MERIT, ASTER GEDM AW3D, and TanDEM-X.

5.2.6.1 Characterization of DEMs (Digital Elevation Model)

- **SRTM (Shuttle Radar Topographic Mission)**

SRTM DEM with 30m resolution has been highly considered in the study because of its capacity to generate the most complete near-global high-resolution digital topographic database and its homogenous and free availability. SRTM was launched in February 2000 by NASA (National Aeronautics and Space Administration) and NGA (National Geospatial-intelligence Agency). After modification, It comprises two parallel single-pass interferometers, a C-band system and an X-band system (L. Yang et al., 2011). Products of SRTM are either InSAR derived or exhibit typical radar artifacts, so it consists of InSAR-caused artifacts like foreshortening, layover, and radar shadow in geometrics data. However, the SRTM 1Arc-second Global offers void-filled data at 30m resolution (SRTM, 2017). The accuracy of SRTM DEM is determined by Shuttle Laser altimeter-02 (SLA-02) data, Different Global Positioning System (DGPS) Ground truthing points, or high accuracy small scale DEMs. It is contributing to several studies involved in gully erosion or land erosion assessment (Al-Abadi & Al-Ali, 2018; Debanshi & Pal, 2020; Shellberg, 2021).

- **ALOS PALSAR:**

ALOS PALSAR was originated by JAXA in a mission in 2006 to contribute to the field of mapping, monitoring of disaster, accurate regional land-cover observation, and resource surveying. ALOS is Advance Land Observing Satellite-1 and PALSAR is one of three instruments (PRISM, AVNIR-2) on the ALOS. PALSAR is a Phased Array L-band Synthetic Aperture Radar that consists of all details in all weather and 24 hours observation (Sena et al., 2020) and also worked as a repeat pass interferometry from 2006 to 2011. PALSAR data came from multiple observation modes with variable polarization (HH or VV, HH+HV or VV+VH, resolution (10m, 20m, 100m, 30m), swath width (70km, 70km, 250-350km, 30km) and off-nadir angle (34.3°). Especially it provides two spatial resolutions of data i.e., high (12.5 m) and low (30 m). ALOS PALSAR is contributing widely to many research for gully erosion studies (Arabameri, Asadi Nalivan, et al., 2020; Chowdhuri et al., 2021; Nitheshnirmal et al., 2019). The present study uses 12.5 m spatial resolution of ALOS PALSAR DEM.

- **ASTER GDEM**

ASTER GDEM (Global Digital Elevation Model) is DEM data, obtained by a sensor (ASTER) that is satellite-borne. It is developed by a collaboration of NASA (National Aeronautics and Space Administration) and METI (The Ministry of Economy, Trade, and Industry of Japan) to cover all the land on the earth. It is DEM data came from the Stereoscopic mode of three nadirs and three backward combined bands correlated with the near-infrared band; It covered almost 99% of the earth's surface from 83° N to 83° S latitudes by its first version released in June of 2009 (Chowdhuri et al., 2021). The DEM data is freely available by the Land Processes Distributed Active Archive Center (LP DAAC) (NASA/METI/AIST/Japan Space systems And U.S./Japan ASTER Science Team, 2009). However, there is a standard deviation of 5.9 to 12.7 meters has been detected in the ASTER GDEM version2 released in 2011 (Chang et al., 2019; Grohmann, 2018). Several recent studies have applied ASTER

GDEM in gully erosion-related studies (Arabameri & Pourghasemi, 2019; Chowdhuri et al., 2021; Garosi et al., 2018). In our study, ASTER GDEM of 30m resolution has been used to compare with the other DEM on Random Forest ML model.

- **AW3D:**

In our study, the AW3D (ALOS World 3D) data with 30m spatial resolution is highly considered. It is the first in the world with the most accurate 3D map provided by 3 million satellite images, the data with the coverage of all global landscapes with 5m resolution. AW3D was jointly developed by NTT DATA, JAXA, and RESTEC (Remote sensing technology center of Japan), in February 2014. MAXAR technology also contributes to this service by providing satellite images with great details from 0.5m to 2m resolution version of 3D map. The enhanced data quality came from its ALOS imagery (Advanced Earth Observing Satellite) also known as 'DAICHI' from JAXA (Japan Aerospace Exploration Agency), which is laced with the optical instrument PRISM (Panchromatic Remote-sensing Instrument for Stereo Mapping). PRISM has the capacity to generate the topographic data with its 3D stereoscopic observation and also it acquires data in three different directions (Forward, Nadir, and Backward), so there is no blind angle; these characteristics make it able to capture the precise data of complex terrain also without any distortion. Precise 3D coordination with high accuracy of Geo-location is the basis of AW3D accuracy, which makes it the world's best satellite technology. The data from AW3D has been widely used in several fields, from disaster management, and environmental monitoring to city planning, and infrastructure to transportation and public health.

- **MERIT:**

MERIT (Multi-Error-Removed Improved-Terrain) DEM was re-formed by eliminating the multiple error components such as tree height bias, absolute bias, stripe noise, and speckle noise) from existing spaceborne DEMS (SRTM3 v2.1 and AW3D-30m v1) with the help of multiple satellite datasets and filtering techniques. It provides the terrain elevation at 90m (3arc-second) resolution at the equator and covers the land areas between 90N-60S, referenced to WGS84 and EGM96 geoid. MERIT DEM has been rarely found in use for gully erosion susceptibility as an elevation. Grohmann, 2018 didn't select the MERIT DEM in their study of evaluation of TanDEM-X with other DEM because of its coarse resolution and low data quality. In this evaluation MERIT, DEM with 90m resolution is employed to test and compare its performance on the Random Forest model.

- **TerraSAR-X/TanDEM-X:**

TanDEM-X DEM or TerraSAR-X is a co-flying radar satellite, it was the mission by German Aerospace Center (DLR) and EADS Astrium (Airbus Defense and Space) with the primary goal to acquire Global Digital Elevation Model with an extraordinary accuracy (12m horizontal resolution and 2m relative height accuracy). Apart from this, it is also aiming to along-track interferometry and new Bistatic and Multistatic SAR technology (Grohmann, 2018; Zink et al., 2014). This flying radar technology is a modern and innovative creation that has been achieved by amplifying the TerraSAR-X SAR (synthetic aperture radar) mission by a second, similar satellite TanDEM-X (TDX) flying and synchronizing in close formation with TerraSAR-X (TSX) (Zink et al., 2014). The TSX was launched on 15 June 2007 and TDX was launched with minor modifications on 21 June 2010. The DEM data service from TerraSAR is contributing to many studies related to Land degradation or Gully erosion topic (Bernini et al., 2021; Bosino et al., 2020; Grohmann, 2018; Raj et al., 2022). This recent study in this chapter has evaluated and compared the 5m DEM of TanDEM-X with the other five DEMs to explore the role of DEM in gully erosion estimation.

5.2.7 Gully Controlling Factors

The selection of gully affecting variables highly controls the production of an accurate gully erosion susceptibility map, yet it is mostly experimental based as there is no standard has been decided for this selection (Conoscenti et al., 2008; Garosi et al., 2018). The range of these variables is wide and highly impactful in the formation, distribution, volume, and velocity of run-off in gully erosion processes (Conoscenti, Angileri, et al., 2013; Valentin et al., 2005). Therefore, its selection is important for developing a good quality factor. In this study, the gully affecting factors chosen was- Elevation, Slope, Aspect, General Curvature, Longitudinal Curvature, Plan curvature, profile curvature, Catchment Area, catchment slope, modified catchment area, LS factor, Topographic wetness index, terrain ruggedness index, Stream Power Index, Flow accumulation, Land surface temperature, Rainfall, NDVI and distance from Rain (Figure 5-5 and 5-6). The topographic variables from all six DEM comprise different values; the same variable for the same location gives different information due to different DEM types (Figure 5-5). The study also discovered that, for some attributes, the high resolution of DEM favors better information, while for some attributes, the lower resolution favors better. It is revealing that the pixel size with respect to the size of the phenomenon is an important aspect of this study. Figure 5.5 shows the gully erosion conditioning factor applied in this study, derived from all Six DEMs using ArcGIS and SAGA GIS for the study area. These factors are-

(a) – Slope, (b) – Aspect, (c) – General Curvature, (d) – Longitudinal Curvature, (e) – Catchment Area, (f) – Catchment Slope, (g) – Modified Catchment Area, (h) – Plan Curvature, (i) – Profile Curvature, (j) – Slope Length factor, (k) –Stream Power Index, (l) – Terrain Ruggedness Index, (m) – Topographic wetness Index, (n) – Positive Openness, (o) – Flow Accumulation

5.2.8 Multicollinearity Scanning

Multicollinearity analysis is a necessary step for selecting effective gully erosion factors and producing accurate GESM. This issue exists when two or more two variables are highly correlated and alter the statistical significance of the result (Arabameri, Asadi Nalivan, et al., 2020). This process is applied to remove the highly correlated factors. Multicollinearity value is determined by the Value Inflation Factor (VIF) and Tolerance (TOL). The VIF > 10 and TOL < 0.1 indicates the presence of a linear correlation between two pairs of gully controlling factors (Dormann et al., 2013; Merghadi et al., 2018; Raj et al., 2022). In this study, R software has been used to fix this problem. However, there are some equations that have been applied to calculate the VIF and TOL (Chowdhuri et al., 2021).

$VIF = 1/TOL$

$TOL = 1 - R_j^2$ (R_j^2 is the coefficient of multiple determination of j on the predictor variables.)

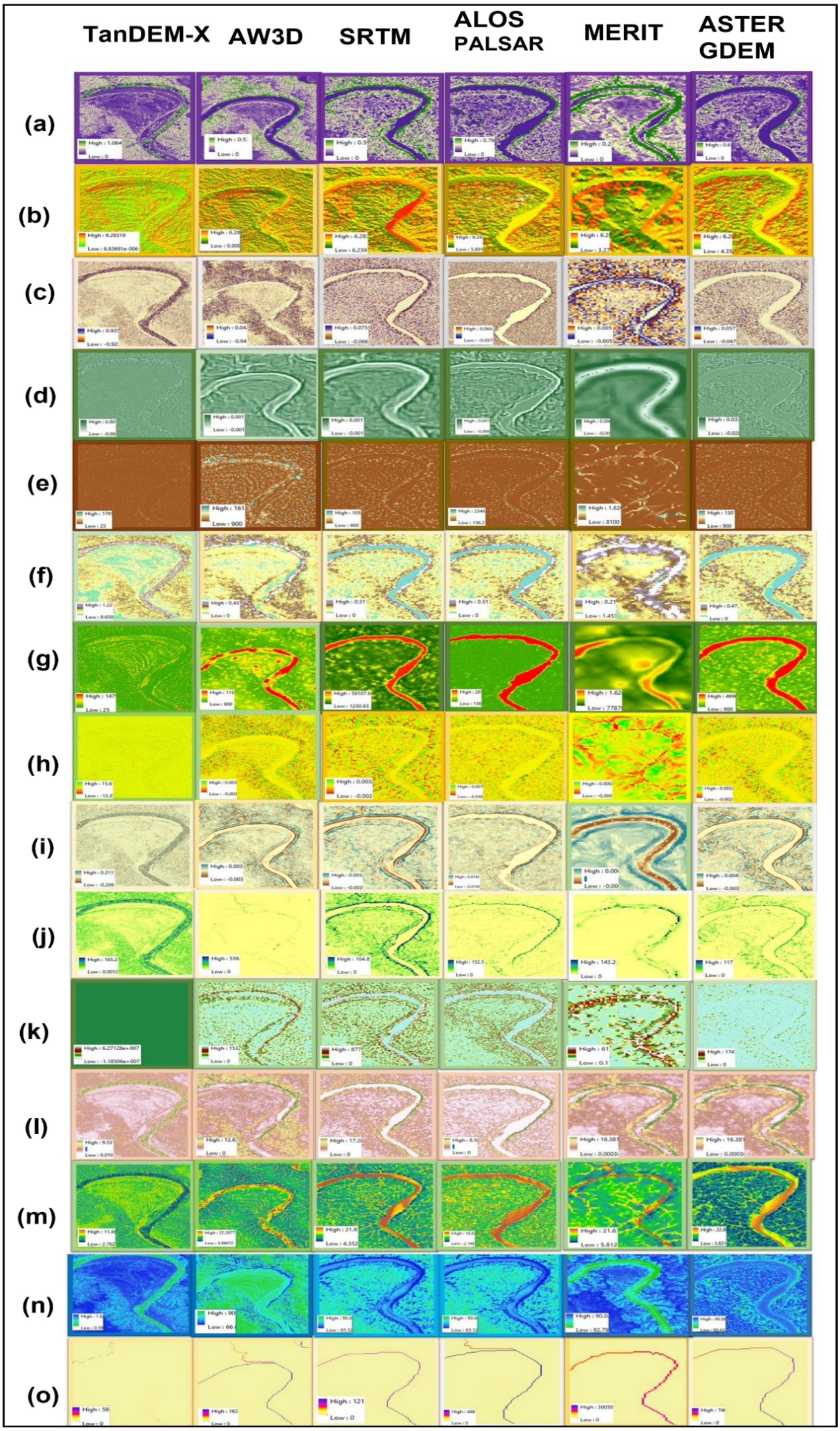


Figure 5-5: Gully erosion conditioning factor derived from all Six digital elevation model

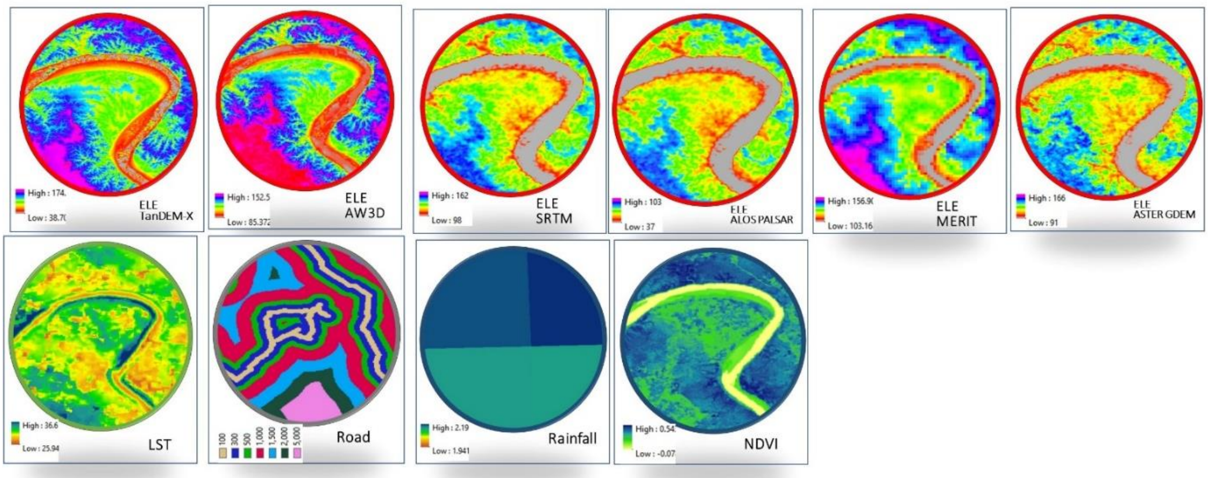


Figure 5-6: Elevation of Six DEM and ancillary factors, (LST- Land Surface Temperature, Road- Distance to Road, Rainfall and Normalize Difference Vegetation Index).

5.2.9 Selection of Random Forest model

The objective of this study is based on DEM effect evaluation, for which Random Forest (RF) machine learning model has been approached as it has been explored in several research and found to be as most efficient and reliable model in gully erosion assessment. I have tested in previous work, RF with four other machine learning models (Logistic regression, Naïve Bayes, Decision Tree, and Artificial Neural Network ANN) to produce the multi-featured gully erosion susceptibility map, in their attempt RF came up with the highest accuracy and ROC value than other four models (Raj et al., 2022). (Avand et al., 2019) compared the Random Forest model with the K-Nearest Neighbour classifier for gully erosion susceptibility and found RF as a better performer with higher accuracy values. Similarly, several recent studies have utilized Random Forest (Arabameri, Pradhan, & Rezaei, 2019a; Gayen et al., 2019, 2020b; Kuhnert et al., 2010) and compared it (Arabameri, Yamani, Pradhan, et al., 2019; Avand et al., 2019; Hosseinalizadeh et al., 2019) on a various scale and parameter gully assessment and declared it most accurate, efficient and flexible model. This ensemble classifier, based on the decision tree, produce thousands of trees and forms a forest for decision making (Rahmati et al., 2017a), it comprises interesting features like low computational cost and also can work with very high dimensional data (Caruana & Niculescu-Mizil, 2006). Random forest is a nonparametric and multivariate model (Breiman, 2001; Rahmati et al., 2017a).

5.3 Result

5.3.1 Multicollinearity Analysis

In the present study multicollinearity test among gully affecting factors was performed in R software. The same gully controlling factors were selected for the study, and as mentioned above (Figure 5-4), the pixel points taken for extracting the value of these factors are also the same. Therefore, the multicollinearity check was done only for TanDEM-X DEM factors because of their strongest influence in the study. Longitudinal curvature, Catchment Area, LS factor, and Terrain Ruggedness show a correlation with the VIF value of 14.48, 22.26, 13.66, and 22.64, respectively (Figure 5-7, Table 5.1). Removal of these factors produced an unambiguous dataset for the subsequent modeling process ahead. Figure 5-8 shows the correlation matrix among the variables after the removal of highly correlated factors.

Table 5-1: Multicollinearity values of factors in the TanDEM-X model

Factors	VIF	Tolerance
DEM	1.82	0.54
SLO	3.56	0.28
ASP	1.01	0.99
LS	13.66	0.07
CAT_S	3.44	0.29
CAT_A	22.26	0.04
G_CUR	7.13	0.14
MOD_C	1.9	0.52
LON_C	14.48	0.06
PAL_C	1.37	0.72
PRO_C	7.54	0.13
SPI	1	1
TRI	22.64	0.04
TWI	4.29	0.23
POS	2.38	0.42
FLAC	1	1
NDVI	1.61	0.62
RAIN	1.04	0.96
LST	1.25	0.8

Factors	VIF	Tolerance
DTR	1.12	0.89

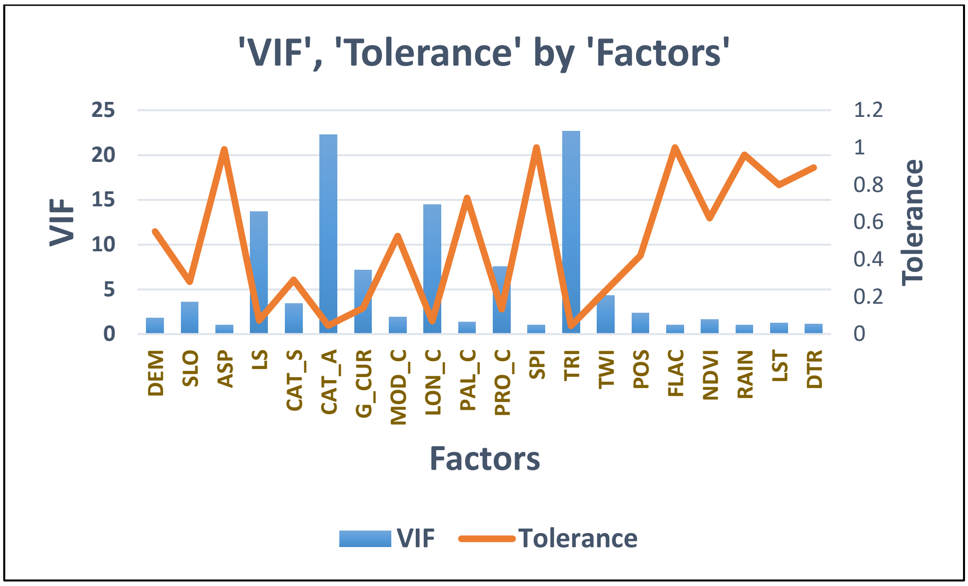


Figure 5-7: Multi-collinearity statistics between Gully affecting factors of TanDEM-X DEM

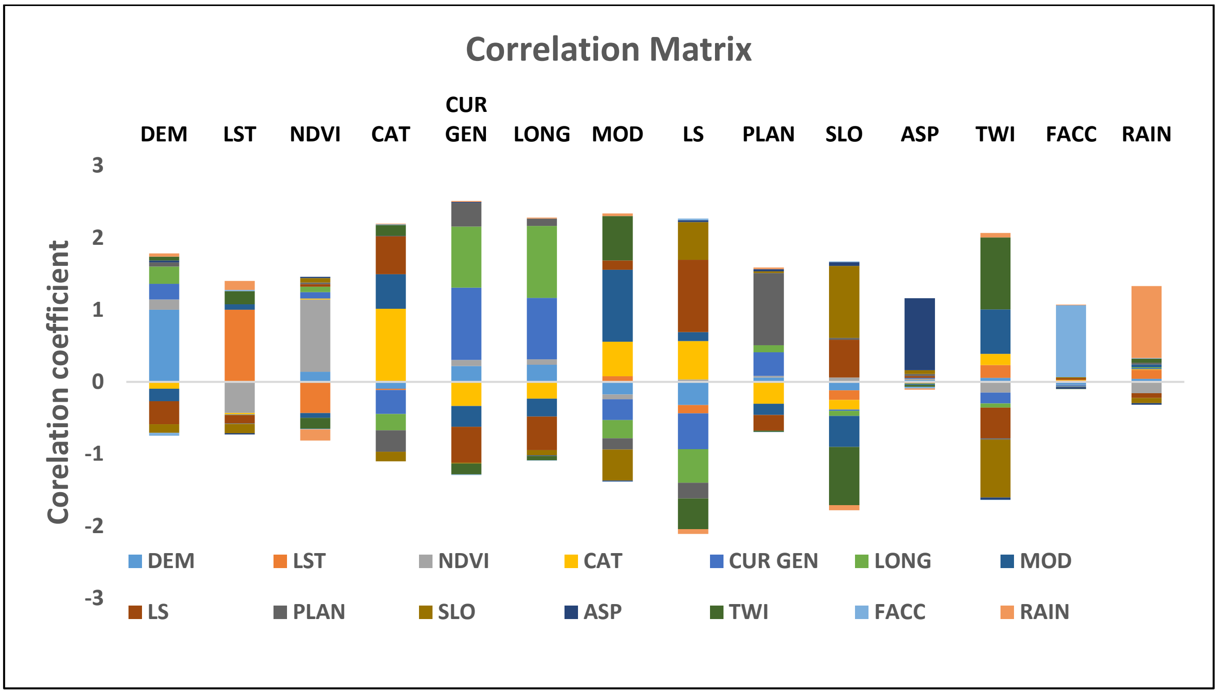


Figure 5-8: Correlation Matrix of multicollinearity of gully erosion affecting factors in the study.

5.3.2 Analysis of contrasting DEM performance

For the study area Gully erosion susceptibility model has been prepared by using six DEM as elevation to examine the role of DEM resolution impact on the accuracy of the model. In this order, 25,000 random pixel points have been taken for all the six DEMs to construct the training model, comprising the value of volume and value of all the gully affecting factors and the spot of gully eroded area and non-eroded area in a binary number (0 and 1). Random Forest has been employed to run the model. The selected DEM performed differently on the RF machine learning simulation and showed various ROC values (Table 5.2, Figure 5-9).

SRTM DEM with 30m spatial resolution and EGM96 corrected data set showed below average efficiency in producing GES map. The ROC or AUC (Area under Curve) value by SRTM is 0.66, whereas the kappa value is 0.24 and Root mean square error (RMSE) is 0.47.

ALOS PALSAR DEM, with the second highest DEM resolution of 12.5m in this study, gave unexpectedly and comparatively very low accuracy on the random forest model with a 0.64 AUC/ROC value. The model's root mean square (RMSE) value is very high, i.e., 0.483, whereas the kappa statistic is 0.21.

Next in the series is ASTER GDEM, derived of 30m DEM resolution showed the lowest accuracy for gully erosion mapping on RF model. The training model built from ASTER GDEM came up with only a 0.63 ROC value, which is the lowest ROC in this study. The kappa value by this is also the lowest i.e., 0.18, whereas the RMSE is the second highest (0.486) in all DEM.

In this study MERIT, DEM Is comprised of the lowest DEM resolution of 90m. Because of its coarse resolution, its training model didn’t perform very efficiently on the RF machine learning platform. MERIT gave the second lowest AUC value (0.64) after ASTER GDEM, while the Root means square error is the highest at 0.489. The kappa value falls at 0.20, the second lowest one (Figure 5-9, table 5.2).

AW3D DEM in this study was accomplished with one of the most accurate gully erosion mappings after TanDEM-X. Despite of 30m spatial resolution (same as SRTM and ASTER GDEM), the ROC value by AW3D is 0.73, which is much higher than above mentioned DEM. Its kappa value is 0.34 and RMSE value is 0.457, predicting the result with high accuracy and validation.

The study applied multi-temporal TerraSAR-X DEM of 5m spatial resolution and achieved the best result. It shows the capability of producing the most accurate Gully erosion Map with the highest 0.87 AUC/ROC value and highest kappa value of 0.73. The DEM has been executed with 97% accuracy on the Random Forest model and has become helpful in the gully erosion estimation of the study area.

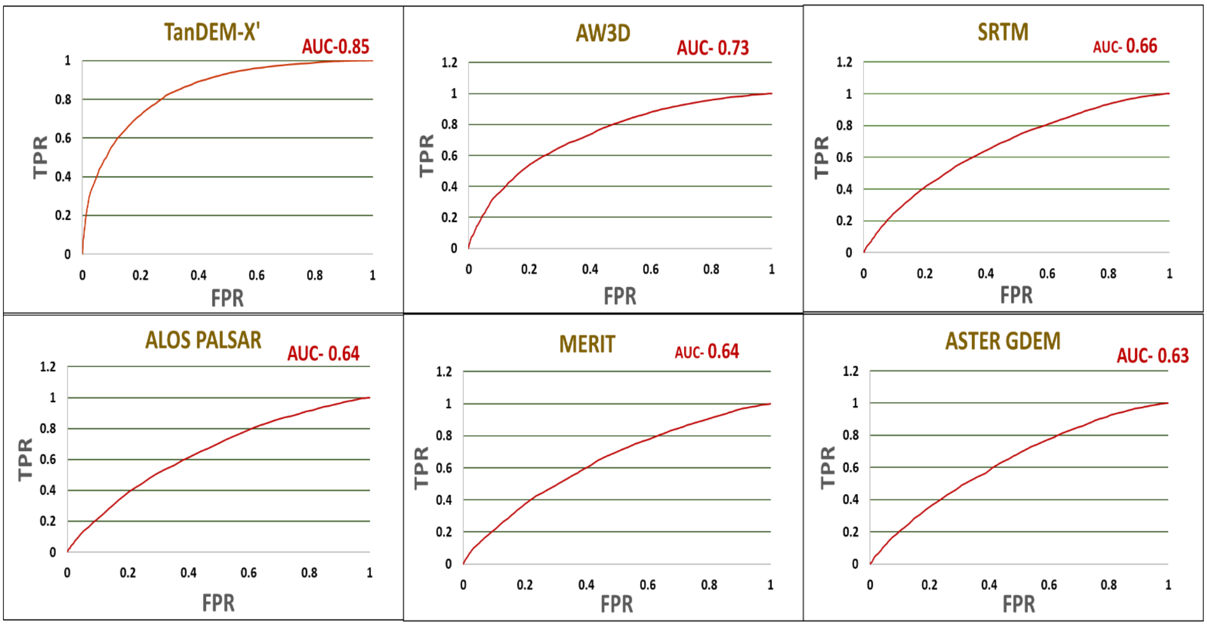


Figure 5-9: The AUC (Area under the curve) and ROC (receiver operating function curve) value obtained for the 6 DEM model on Random Forest machine learning. (TPR- True positive rate, FPR- False positive rate)

Table 5-2: Evaluation matrix of six selected DEM models on Random Forest using 250000 random sets of training points

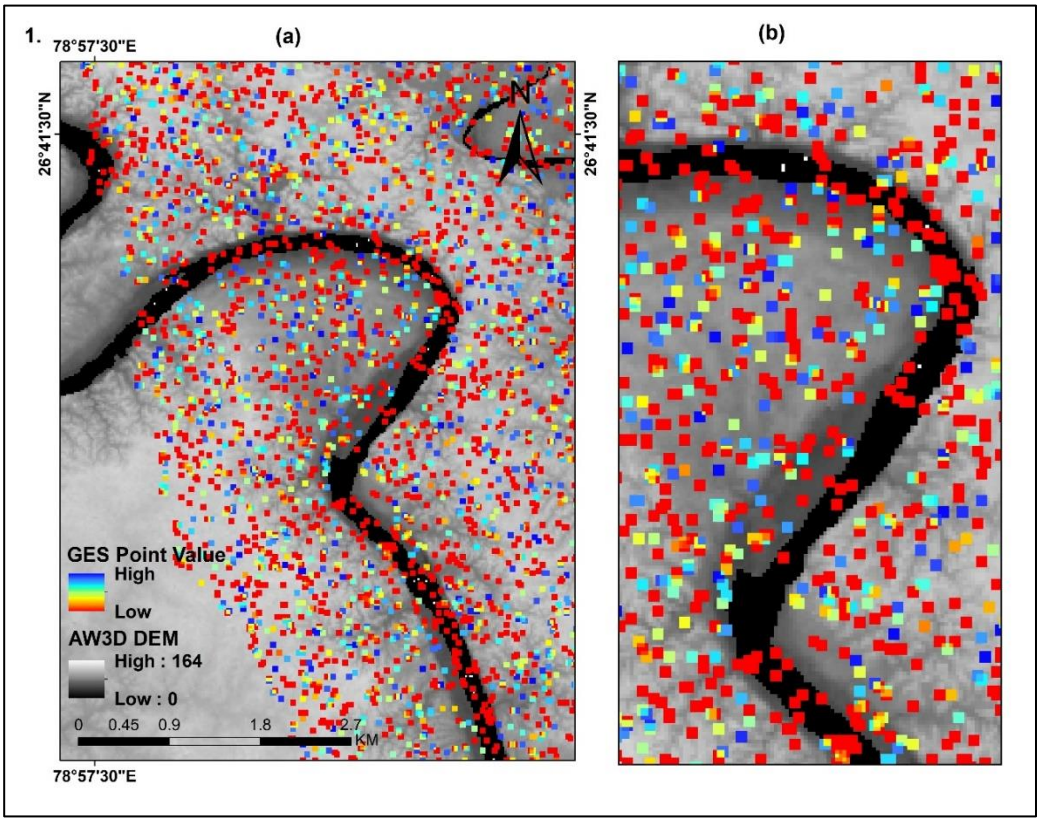
Evaluation Criteria	DEM (Training Set for Random Forest model) 10-fold cross validation					
	TanDEM-X	AW3D	SRTM	ALOS PALSAR	MERIT	ASTER GEDM
AUC/ROC	0.85	0.739	0.669	0.647	0.640	0.635
RMSE	0.41	0.454	0.477	0.483	0.489	0.486
Kappa	0.53	0.34	0.24	0.21	0.20	0.18

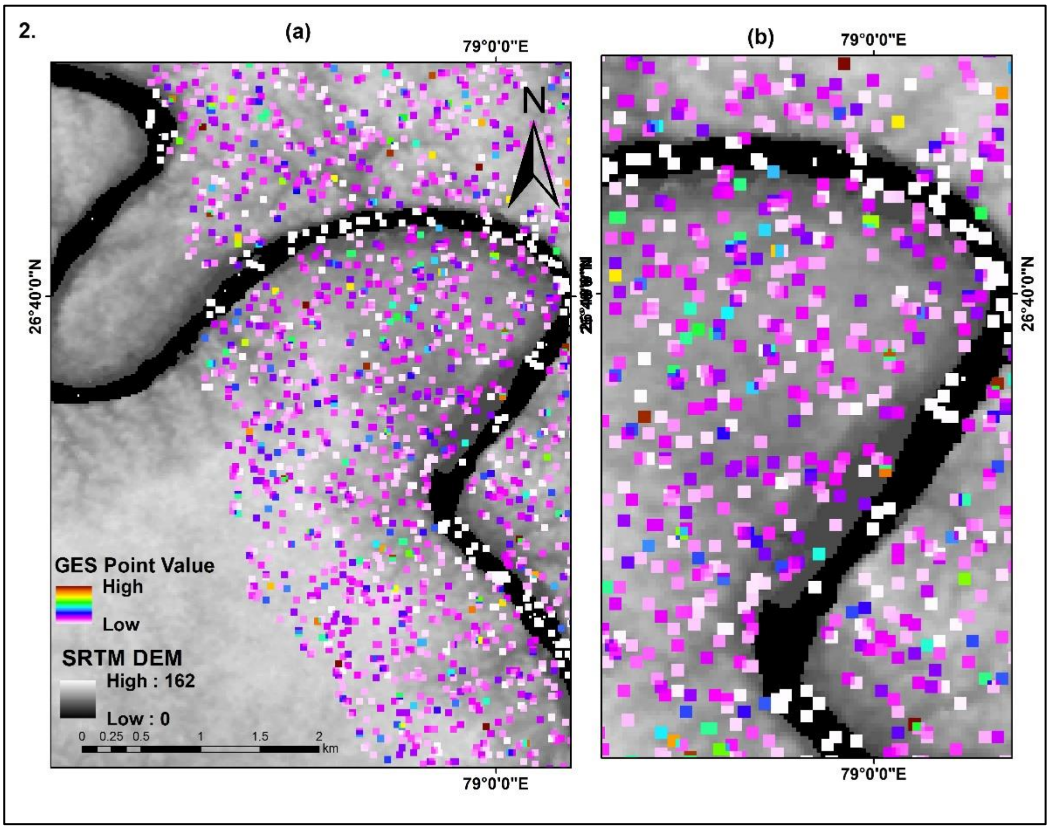
5.3.3 Gully Erosion Susceptibility Mapping

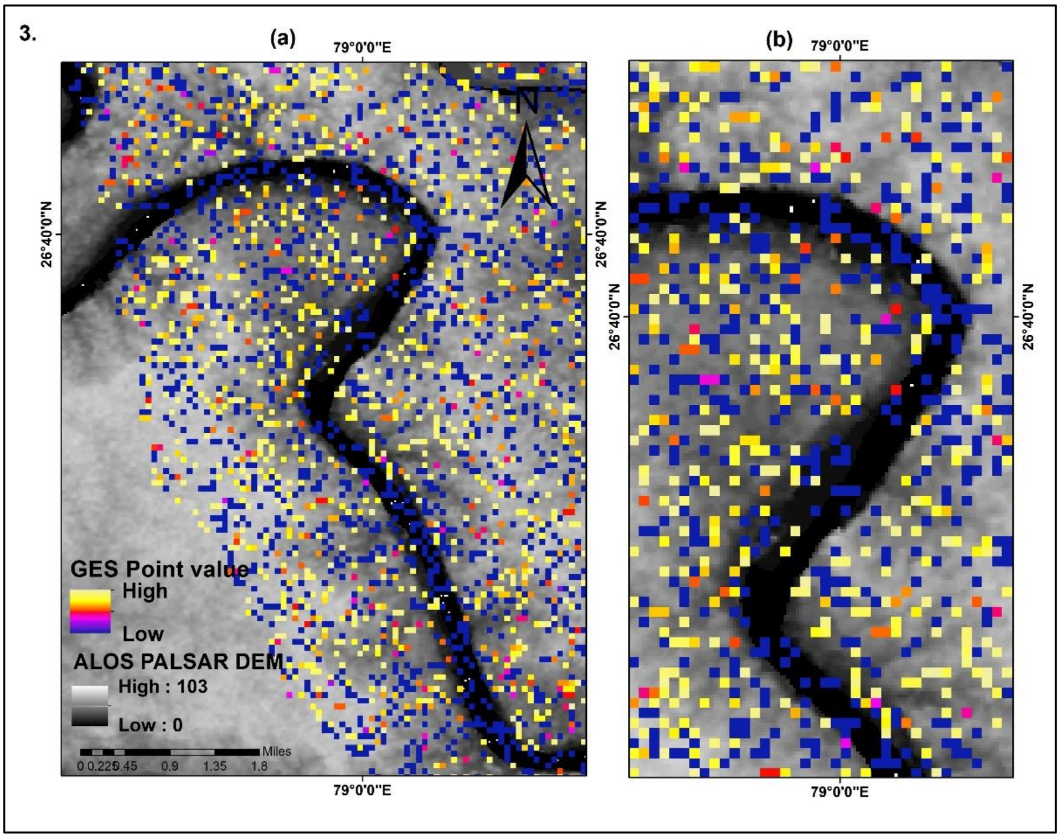
Following the evaluation process, the gully erosion susceptibility map was generated by using all DEMs. Figure 5-10 (1 to 5) is a gully erosion susceptibility map based on DEM

AW3D, SRTM, ALOS PALSAR, MERIT and ASTER GDEM, respectively; where the prediction of gully erosion location has been indicated in pixel point value. The susceptibility value of the same pixel point of the same location in the map varies from high to low because of different DEM sources and various resolution scales.

Figure 5-11 is presenting GESM based on TerraSAR-X/TanDEM-X model. The DEM came up with the highest accuracy or ROC value (0.85) and was approved for superior potential in producing a robust erosion susceptibility map. This map deducts the possibility of gully erosion all over the study area by using topographic values for all the pixel points of the area. In the map, the presence and absence of active gully erosion spots in the study area have been presented in the form of 0 and 1, the binary number. The gully erosion susceptibility map for the study area, shown in Figures 5-11, is calculated as the probability of active erosion in the area. The estimated area that fell into the zone of gully erosion is 52.67 km$^{2.}$ Out of 131 km^2 areas, estimating 40% of the area is the victim of gully erosion. The estimated map has been reclassified on the equal interval with the help of ArcGIS, from very low (0.0-0.2), low (0.2-0.4), medium (0.4-0.6) to high (0.6-0.8) and very high (0.8-1.0). The result concludes that the study region is highly vulnerable to active gully erosion, which needs to be mitigated and restored by effective actions and planning. Hence, the efficient and advanced tools and methods proposed in this study should be more utilized and explored.




2.
(a)
(b)
79°0'0"E
26°40'0"N
N
GES Point Value
High
Low
SRTM DEM
High : 162
Low : 0
0 0.25 0.5 1 1.5 2 km


3.
(a)
(b)
79°0'0"E
26°40'0"N
N
GES Point value
High
Low
ALOS PALSAR DEM
High : 103
Low : 0
0 0.225 0.45 0.9 1.35 1.8 Miles

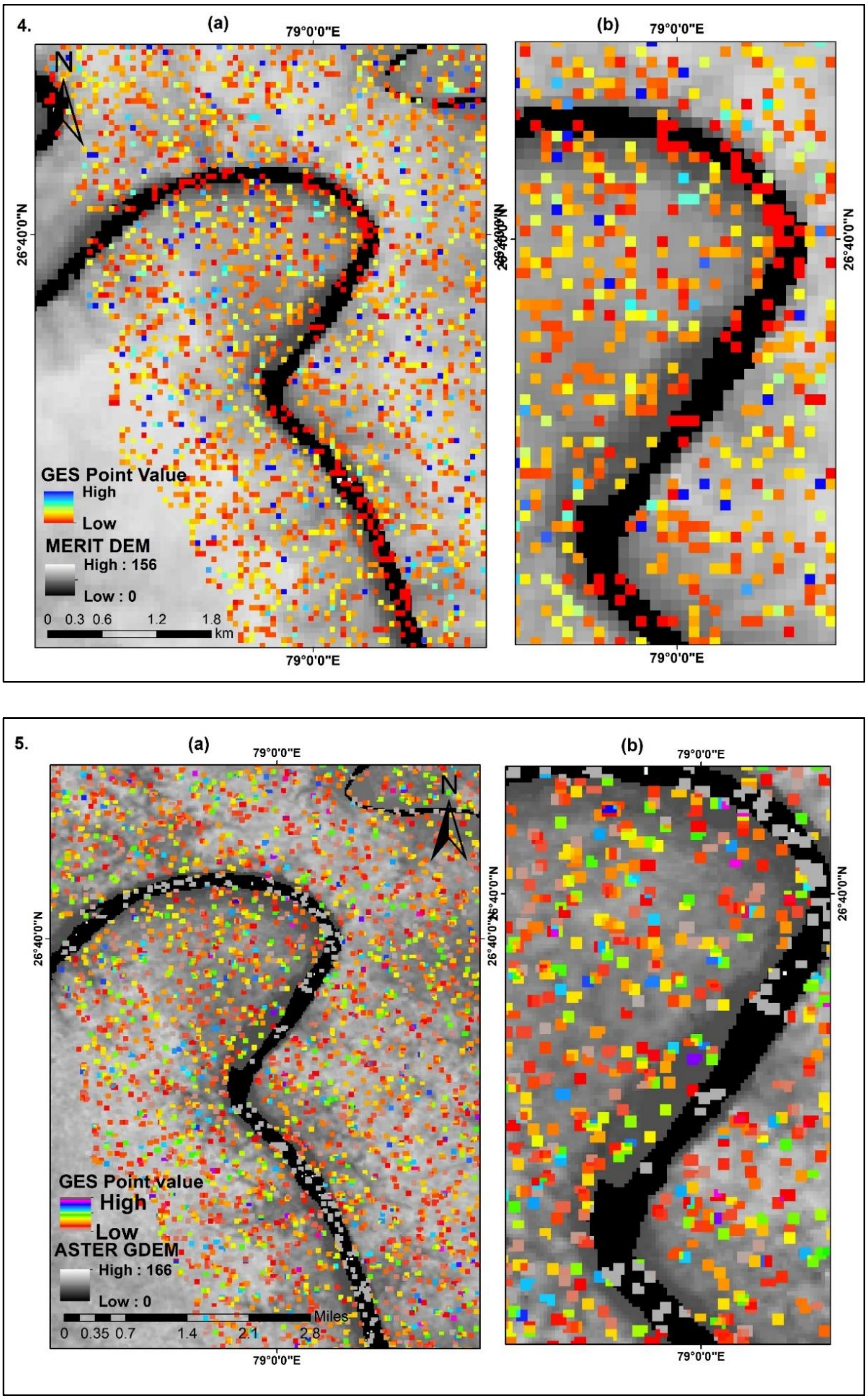


Figure 5-10: (1-5). Gully erosion Susceptibility map was deducted by using five DEM for the study area, showing in form of erosion-point value difference. (a) Erosion susceptibility location (b) Zoom extent of location.

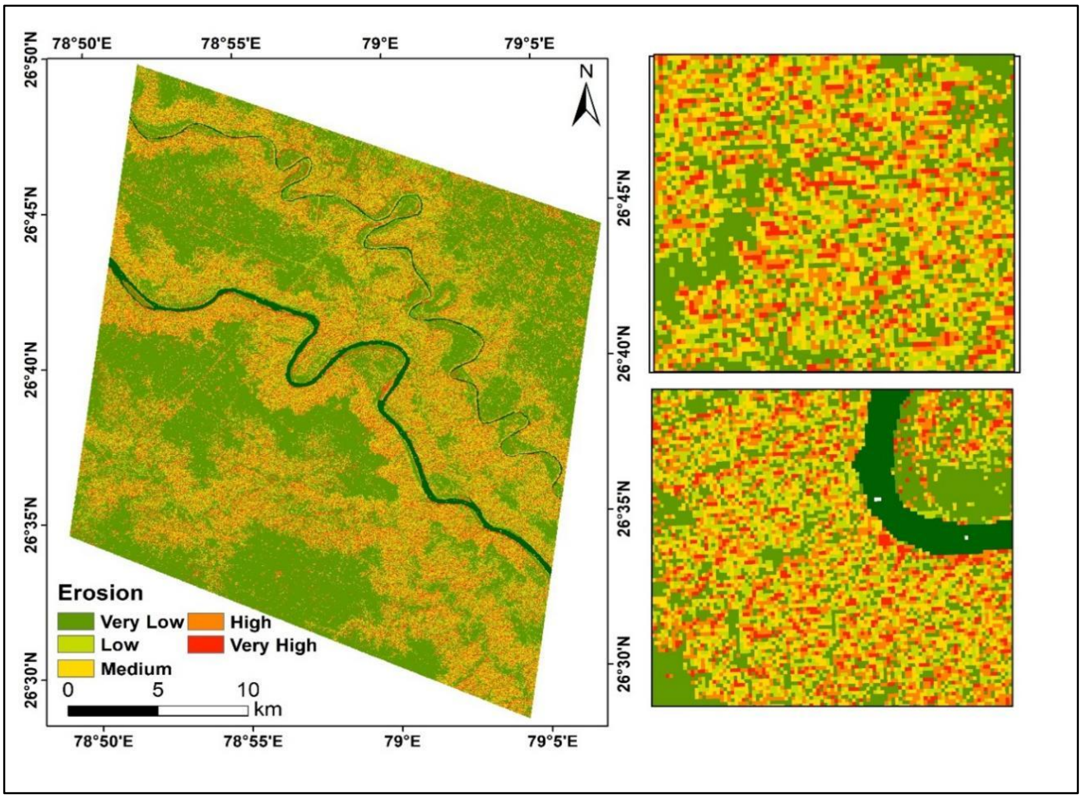


Figure 5-11: Gully erosion susceptibility map prepared with the help of TanDEM-X model for the whole study area, showing the presence of gully erosion in the area ranging from very low to very high.

5.4 Discussion

5.4.1 Effect of DEM resolution and data quality on susceptibility model

Gully erosion susceptibility is the most crucial step in the path for ravine reclamation and mitigation. Several studies have been involved in this field to build an accurate gully erosion susceptibility map by using geospatial data and machine learning; still, there is lacking a clear understanding of the usage of optimal grid resolution of DEM in this process. Gully erosion is a complex natural process and is stimulated by various geo-environmental variables; therefore, the quality of these data plays a vital role in making the promising GES model with the help of GIS and Machine Learning. Recently, machine learning techniques have gained popularity among researchers working in this field and proved themselves more accurate and efficient in gully erosion susceptibility assessment. However, the input data set is an essential element for better performance by machine learning which is mostly provided by DEM (Chang et al., 2019; Szypuła, 2019). DEM provides most of the important information like- terrain information, erosion controlling factors, hydrological factors, and also environmental variables.

All of these factors derived from DEM are highly affected by DEM type and resolution (W. Zhang & Montgomery, 1994), the change in grid resolution affects the value of these gully affecting factors (J. X. Zhang et al., 2008). DEM-driven topographic information details lie in its spatial resolution(W. Zhang & Montgomery, 1994). Every resolution category has its conditions and requirements; for example, if we go for higher resolution, it needs more computational work for pre-processing of data (Chang et al., 2019), and if we choose lower resolution DEM, the quality of topographic information will be sacrificed especially in the case of primary topographic attributes like slope angle and curvature. Thus, the selection of optimal DEM resolution is the primary step.

In this way, the spatial resolution of DEM can influence the ML model in achieving the expected result. And like several studies, Raj et al., 2022 have tested and compared the Random Forest model with other ML models and found RF as the best model with the highest accuracy for GES. In this regard, the present study has tried to evaluate the importance and effect of DEM and its data quality on RF model accuracy for GESM. The study has tried to check the changes in the accuracy of the RF model with the different DEM resolution ranges. This study has considered six DEMs; the three DEM, SRTM, ASTER GDEM, and AW3D have 30m of the resolution, ALOS PALSAR has 12.5m resolution, MERIT is comprised of 90m resolution and TanDEM-X resolution is 5m. TanDEM-X or TerraSAR-X with 5m grid resolution gave the expected highest accuracy with 0.87 ROC value on the RF model for gully erosion susceptibility of the study area. However, TanDEM-X is not freely available and is commercially available. The other DEMs in this study, which are freely available, are lower resolution compared to TanDEM-X and have shown less accuracy on RF. Even the three DEMs of 30m spatial resolution (AW3D, SRTM, and ASTER GDEM) perform differently and give different ROC values. AW3D gave the second-best result in the study and came up with a 0.73 ROC value because of its high-quality data with the world's most accurate 3D map provided by 3 million satellite images. The actual optical resolution of AW3D is 2.5/5m; on the other hand, SRTM with the same 30m resolution put up only 0.66 ROC value, very less accuracy in modeling, which cannot be considered producing GESM. ASTER GDEM, also with 30m grid resolution, is the least efficient with the lowest ROC value in this group and the whole series.

The outcome is contrary to Bouaziz et al., 2011, where ASTER DEM and SRTM were combinedly and used to predict the gully erosion feature by employing SVM (support vector machine), MLC (Maximum likelihood classification), and MD (Maximum Distance). MERIT DEM provided the second-lowest accuracy or ROC value with 90m spatial resolution, it is the

DEM with the lowest grid resolution. It is described that probably lower resolution, the bigger pixel size is not ideal for the study of a finer process like gully erosion on land. In this case, the pixel size is much bigger than the gully size, which could not provide proper attribute information. However, the most interesting result was shown by ALOS PALSAR, with the second-highest DEM resolution in this series at 12.5m. ALOS PALSAR with higher resolution unexpectedly came up with very low accuracy on RF, which contrasts with Arabameri et al., 2020; Arabameri, Pradhan, et al., 2019b, where both the studies have applied ALOS PALSAR and found good results. However, both of the studies have employed an ensemble ML model (two or more than two ML models together) and predicted the gully erosion. The probable reason for this result is that the ALOS PALSAR has L-band sensors, which is not considered ideal for studying ravines like bare land. This prediction is making the idea about the role of sensor type used with land type in extracting the attribute features.

The study shows that the finer resolution of DEM along with sensor type significantly influenced the quality of data required for the gully erosion modeling. On the other side, the lower resolution does not help in increasing the model accuracy for GES, probably because the lower DEM resolution does not provide precise attribute information. Gully erosion is a very fine phenomenon that is based on the geo-morphological processes of that area. Therefore, the gully erosion susceptibility assessment is highly controlled by morphology measured at the micro-scale level. Therefore, high-resolution DEMs are ideal for topography variations at the micro-scale, which is suitable for scrutinizing fine processes like gully erosion.

5.4.2. Significant

Selection of the ideal DEM and its optimal resolution is the most crucial part of machine learning-based gully erosion assessment. The study in this chapter is devoted to making an understanding regarding the Importance of the Digital Elevation Model (DEM) in gully erosion study and the selection of suitable DEM with the suitable resolution for monitoring gully features. The results from this study can be significantly used in decision making during pre-processing part, for example, TanDEM-X with 5m of the higher resolution is approved as the most ideal DEM for gully erosion assessment but this DEM is not freely available and is expensive, hence AW3D DEM with 30m of resolution can also be an alternative option because it came up with the highest accuracy after TanDEM-X. on the other hand, DEM with a very low resolution like 90m of grid size cannot be useful in gull erosion study as the big pixel size is not precise in giving accurate information about finer features like gullies. Hence, the present study of DEM resolution effect analysis is a contribution to the methodological development of gully erosion assessment.

5.5. Conclusion

GIS and Machine Learning based gully erosion mapping is an emerging technique and compiled with many possibilities. Recent studies have efficiently applied these methods in generating very accurate GESM. However, this technology is composed of several fine steps and pre-processing, where the most crucial step is the filtrations of good quality and important data for input. Especially the data of attribute or terrain and environmental variables are controlling factors of gully formation type geo-morphological process; thus, these are key elements in GESM. The quality of data and information that lies in it, highly depends on DEM features i.e., Spatial resolution, satellite, and sensors. This research analyses the significance of DEM resolution in GESM; the approach is based on Random Forest. The result of this evaluation is concluded in the following key points:

- The resolution and source DEM has shown a remarkable effect on the accuracy of the Random Forest model in gully erosion assessment. In addition, it has a high impact on the value of gully affecting factors.
- Applied DEM with higher resolution does not compulsorily perform more efficiently than DEM with lower resolution, the sensors and other features of the satellite are also observed to be influential in the quality of geo-morphological data and GESM validity.
- The accuracy of SRTM, ASTER GDEM, and AW3D with the same grid resolution vary in terms of ROC value on the RF model. AW3D came up with the highest ROC value in all three and second-best in the whole series, whereas ASTER GDEM gave the lowest ROC value in this whole evaluation and SRTM also did not fulfill the expected outcome.
- MERIT DEM, with the lowest resolution scale of 90m showed very little accuracy with the second-lowest ROC value here.
- The most unusual result was revealed by ALOS PALSAR in this line, the DEM with a higher resolution of 12.5m bring up with very less ROC value on RF and was not found as very accurate for gully mapping.
- TanDEM-X, the DEM with the highest grid scale in this series, appeared with the highest ROC value and gave the best performance in the estimation of gully erosion.
- GESM constructed by using TanDEM-X predicts that the study area is affected by the gully erosion process and needs efficient action to mitigate and restore the land.

Chapter 6: Conclusion and Contribution

Ravines in Chambal Badland represent one of the world's worst forms of land degradation. The alluvial soil of Chambal valley is ever prone to erosion, and it is still expanding. This hazard is associated with environmental as well as socio-economical destruction. Several ravine reclamation programs have been initiated and implemented by government (state & central) and international organizations to control the threats of ravine and gully erosion. Despite the concern for land restoration and soil conservation, the scientific approach that executes the reclamation plan is lacking. The more the area needs ecological and economic development the less it is scientifically explored. In this process, investigation of land, surveying, and planning is the first step (Gupta, 2016), plus the identification of the main gully is essential for the treatment of deep ravines (G. P. Verma et al., 2018). Focusing on these requirements of land investigation and main gully identification, the present study has made attempts toward assessment of gully erosion susceptibility, gully erosion rate, and evaluation of change in volume due to gully erosion. In addition, the study has also explored the use of remote sensing and machine learning in this approach and successfully constructed the methodology to estimate the gully erosion volume change and gully erosion rate using GIS and machine learning. This study has implemented the new and advanced technology of remote sensing and machine learning. This idea is especially very useful for the assessment of deep ravines area, which is not possible to access for the study based on a field visit and field surveying.

6.1. Key Findings and Conclusion

This section has summarised the key findings and conclusions based on the goal and objectives of this study (Section-1.6.). The experiment and evaluations in this study have led to several scientific findings, which have been included in the following points.

- **Chapter-3**: The literature review in this study concludes that there is a study lacking gully erosion assessment in the Chambal ravines of India, especially lack of use of advanced technology like GIS and machine learning for gully erosion monitoring.
- **Chapter-4:** Study in Chapter 4 is based on Goals no.- 1 and 2 of this study (Section-1.6.) and concluded with the following finding.

1) In this study, the Random Forest model is approved as the best model with the highest accuracy for gully erosion susceptibility mapping when compared with some other machine learning models

2) The gullies of the Bhind region showed that there is the presence of active gully erosion, which may cause extend in the ravines or can cause more deepening of the ravines. In addition, the area is highly prone to soil erosion. The average soil erosion volume is 135×10^5 m^3, and the average soil erosion rate is ~283 t ha^{-1} yr^{-1}.
3) The current study successfully predicted the change in volume of the selected area due to gully erosion with the help of GIS and machine learning. Especially the north-northeast location is severely affected by gully erosion, whereas the southwest part of the area shows less volume change by the gully erosion process.
4) The research outcome and methodology in this chapter can potentially contribute to the land investigation process in the ravine's reclamation program.

- **Chapter 5:** This chapter focuses on Goal no.-3 mentioned in Chapter 1 of this thesis. These are the following key findings concluded by this chapter.

1) The resolution and source of DEM have shown a remarkable effect on the accuracy of the Random Forest model in gully erosion assessment. In addition, it has a high impact on the value of gully affecting factors.
2) Together with DEM resolution, sensors and other features of DEM sources were also found to be influential in the credibility of gully erosion susceptibility mapping. However, the higher resolution gives higher accuracy in the study of a finer phenomenon on land like gully erosion but not compulsorily, other characteristics of DEM are also significant.
3) The DEM with very low resolution also failed to give higher accuracy on machine learning modeling, because the very big grid size cannot give the information of finer features on land.
4) The study in this chapter shows the importance of DEM and machine learning models in assessing gully erosion. It can be useful in making a concept for the selection of DEM for the erosion susceptibility pre-processing step.

6.2. Contributions of the Study

The followings are the scientific, environmental, and social contributions of this study.

1) Scientific Contribution

The disastrous consequences of ravine and gully erosion on the environment and people in Chambal Badland are already discussed in Chapter 2. The hazards of ravines can be constrained by ravine reclamation actions (Section-2.10.). But because of a lack of scientific approach in the previous ravine reclamation program, the effort did not succeed. Soil conservation scientists involved in ravines reclamation projects in India (Gupta, 2016; G. P. Verma et al., 2018, from Indian Council of Agricultural Research, ICAR) have mentioned that land investigation, land surveying, identification, and measurement of deep ravines are the primary and crucial steps for any ravine reclamation plan. This study is mainly dedicated to gully erosion susceptibility, gully erosion rate estimation, and erosion volume change quantification with the help of the advancement of remote sensing and machine learning; hence the idea, concept, methodology, and outcome of this whole study can significantly contribute in the primary steps such as- land investigation and surveying, deep ravine identification and measurement, monitoring of gully erosion intensity and the situation in ravines area and related actions of scientific ravine reclamation approach. The research framework constructed in this study is especially significant for gully erosion assessment in the absence of field surveying opportunities because the deep ravines area in Chambal valley is not easily accessible (Pani, 2016).

The recent ravine reclamation program NICRA (National Initiative on Climate Resilient Agriculture), initiated by the government of India under ICAR (Indian Council of Agricultural Research), is funding some research work regarding the management of deep and very deep ravines for the environment and food security. In the list of funded research work (Section-2.10.2), there is also the research area mentioned for *Checking of gully advancement* and *Steep bed of the main gully;* one of the focuses of the present study (gully erosion volume change estimation and gully erosion rate estimation) is very similar to these both proposal and it can effectively contribute to checking of advancement and extension of gully and ravine. Moreover, this study has also analysed gully controlling factors, where the slope degree more prone to gully erosion has been evaluated, this part of the study can contribute to the research goal of the *Steep bed of the main gully* by NICRA.

The methodology and idea provided in this study can also help the researcher and scientific community involved in the ravine and gully erosion study. Furthermore, the whole study and result can help as first-hand scientific information on ravine conditions in the study area to the land reclamation plan designer, policymakers, geologists, soil scientists, and agricultural officers.

2) Social Contribution

The socio-economic condition of Chambal Badland has already been discussed in Section 2.9. of Chapter 2. In this area, the livelihood opportunities of people, their income, food security, education, health system, infrastructure, and heritage agricultural land are all constantly vulnerable and destructed by ravine and gully erosion. This problem can be managed and mitigated by ravine reclamation actions; in the above section, This study can be useful in ravine reclamation programs. In this way, the study is contributing directly to the social and economic upliftment of people in the ravines of Chambal valley.

3) Environmental Contribution:

There are various environmental problems created by ravine and gully erosion, specifically in my study area. These hazards are mostly related to the destruction of land fertility, disturbance of hydrological function, and sedimentation on land and in water bodies (Section-2.8.). Ravine reclamation programs by government and international agencies are continuously working on the environmental restoration of places under ravines. NICRA especially focuses on environmental security from the ravine and gully erosion in the Chambal ravine, including the Bhind region. The previous section focuses on how this study can contribute to the research program of NICRA for environmental security. This study can make an impactful contribution to the ecological and environmental restoration of the Chambal ravine.

6.3. Significance of Study

The study area in the current research is the most extensive zone of Badland in India. The ecological and economic condition of the area is at high risk of degradation. The quality of human life quality in this area is very retarded and mostly based on agricultural income, which is constantly destructed by gully erosion. The area is also defamed as the criminal’s favorite hiding spot, which affects the development of the area. Recently, the government and local community is effectively involved in restoring the land degradation and ravines reclamation. This study is significant for authority in land restoration and reclamation action plans. The estimated gully erosion induces changes in the region and rate of erosion with the methodology and idea of the selection of fine data proposed in this study can play a key role in the assessment and management of ravines during ravine reclamation plans. Section 2.10.3 have recommended some crucial approach that should be taken in ravine reclamation plans, where this study can contribute to the primary step of the "Treatment of deep ravine" section.

6.4. The novelty of the study

- The study attempts a novel approach to the prediction of gully erosion volume change in the Chambal ravines
- The study successfully estimated the gully erosion rate in the Chambal ravines by using GIS and Random Forest model
- The study has developed the methodology for gully volume change mapping and erosion rate estimation by using TanDEM-X DEM and a machine learning model.
- DEM resolution effect evaluation is also a contribution to methodological development for gully erosion assessment study.

6.5. Future Work

The methodological framework presented in this research using GIS and machine learning techniques can also be applied to other areas of Chambal to detect the unexplored dynamics of gully erosion and ravine and have the potential to play a key role in monitoring and management, especially the inaccessible ravines. The study can also recommend some more research based on an idea generated during discussion and suggestions from experts in this field, such as sediment load analysis in the Chambal River and watershed area by using SAR data and a machine learning model. A study of the effect of wind direction on rainfall direction in the gully erosion process is also one of the research recommendations that came from this study.

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Achievements during PhD

Publication:

- Raj, R., Yunus, A. P., Pani, P., & Avtar, R. (2022). Towards evaluating gully erosion volume and erosion rates in the Chambal badlands, Central India. Land Degradation & Development, 1–16. https://doi.org/10.1002/ldr.4250
- Chakraborty, S. Avtar, R.; Raj, R.; Thu Minh, H.V. Village Level Provisioning Ecosystem Services and Their Values to Local Communities in the Peri-Urban Areas of Manila, The Philippines. Land 2019, 8, 177. https://doi.org/10.3390/land8120177

Expected Publication

- Raj R, Yunus, A. P., Avtar Ram. Evaluation of Dem scale effect on Gully erosion susceptibility mapping: approaches based on random forest modeling. Land Degradation & Development (Finalysing for submission)
- Raj R, Yunus, A. P., Avtar Ram. Review of Remote Sensing and Machine Learning approaches for Gully erosion susceptibility from Geo-spatial data. (Finalysing for submission)

International Conferences:

- Raveena Raj, Ram Avtar, Yunush Ali Pulpadan. Study of Geo-morphological changes in Chambal Ravine of India using TanDEM-X SAR and machine learning model. Indian Scientist Association in Japan (ISAJ) 12th Annual ISAJ Symposium, Online & at Tokai University Marine Science Museum. 26th-27th Nov. 2021
- Raveena Raj, Ram Avtar, Yunush Ali Pulpadan. Gully Erosion Susceptibility and Volume Estimation Using TanDEM-X SAR and Machine Learning Model for Chambal Ravine of India. 3rd Global Land Program (GLP) Asia Conference 2021(14th-17th Sep 2021).
- Raveena Raj, Ram Avtar (2021) Monitoring of ravenous land with the TanDEM-X SAR data in central-north India. . 29th IIS Forum “Earth observation, disaster monitoring and risk assessment from space”, 2021 (Online), University of Tokyo, Japan (4th – 5th March 2021).

- Raveena Raj (2020) student session participation. Knowledge Sharing Symposium on Machine Learning and Deep Learning in Geoinformatics-2020, Hokkaido University, Japan (30Nov-3 Dec 2020). (Received Best Presentation Award)
- Raveena Raj, Ram Avtar (2020) Assessment of Ravenous area using Geospatial data and socio-economic survey: A case study of Bhind district of Madhya Pradesh. Young Sustainability Symposium (YSS)-2020, Hokkaido University, Japan (3-5 February 2020).
- Raveena Raj, Ram Avtar (2020) Monitoring of ravines and gully erosion using remote sensing and GIS in last few decades: Review. 11th ISAJ Web Annual Symposium 2020. Innovations in Science and Technology for New Issues and Challenges, Japan, Zoom platform (4-Dec 2020).

Awards and Other Achievements

Awards:

- Best Presentation award: Hands-on Google Earth Engine Training. At the 2020 Knowledge Sharing Symposium on Machine Learning and Deep Learning in Geoinformatics held online from 30th November to 3rd December 2020.

Scholarship:

- Qualified for DX (Digital Transformation) doctoral fellowship from Hokkaido University, October 2021.
- Scholarship from Japan Student Service Organization, JASSO, March 2020.
- Scholarship from Zonta Women's Club, Hokkaido, Japan, December 2021.

Others:

- Research Assistantship at Hokkaido University, January 2021