

Faculté des bioingénieurs

Characterization of gully erosion by remote sensing in Haiti

The case of the Grande Rivière du Nord watershed

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LIST OF ABBREVIATIONS AND ACRONYMS

ADS	Airbus Defence and Space
AI	Artificial Intelligence
ANN	Artificial Neural Networks
API	Automatic Programing Interface
CART	Classification and Regression Trees
CNIGS	Centre National de l'Information Géo-Spatiale
CNN	Convolutional Neural Network
CSV	Comma Separated Value
DEM	Digital Elevation Model
DSM	Digital Surface Model
DT	Decision Trees
DTM	Digital Terrain Model
ELI	Earth and Life Institute
ESRI	Environmental Systems Research Institute
FAMV	Faculté d'Agronomie et de Médecine Vétérinaire
FCIR	False Color Infrared
FN	False Negative
FP	False Positive
GLCM	Grey Level Co-occurrence Matrix
GLDV	Grey Level Difference Vector
GPS	Global Positioning System
GRET	Groupe de Recherche et d'Echanges Technologiques
IDB	Interamerican-Development Bank
IHS	Intensity, Hue, Saturation
IRATAM	Institut de Recherche et d'Appui Technique en Aménagement du Milieu
LiDAR	Light Detection and Ranging
MARNDR	Ministère de l'Agriculture, des Ressources Naturelles et du Développement Rural
MDE	Ministère de l'Environnement
MRS	Multiresolution Segmentation
MS	Multispectral
MUSLE	Modified Universal Soil Loss Equation
NDSI	Normalized Difference Soil Index

NDVI	Normalized Difference Vegetation Index
NIR	Near-infrared
NITF	National Imagery Transmission Format
OA	Overall Accuracy
OBIA	Object-Based Image Analysis
PA	Producer Accuracy
Pan	Panchromatic
PITAG	Programme d’Innovation Technologique en Agriculture et Agroforesterie
PIXA	Pixel-based Image Analysis
RF	Random Forest
RGB	Red, Green, Blue
RPC	Ratio Polynomial Coefficient
RUSLE	Revised Universal Soil Loss Equation
SAVI	Soil-Adjust Vegetation Index
SPOT	Satellite Pour l’Observation de la Terre
TIFF	Tag Image File Format
TN	True Negative
TP	True Positive
UA	User Accuracy
UCLouvain	Université catholique de Louvain
USLE	Universal Soil Loss Equation
UTM	Universal Transverse Mercator
WGS84	World Geodetic System 1984

1. INTRODUCTION

1.1. Background

Soil erosion refers to the process of detachment and transport of solid particles from the soil, primarily driven by water and wind (White, 2006). It is a natural process that transforms soil into sediment, but it can be accelerated by human activities, especially in sloping areas with high rainfall (Weil and Brady, 2017). The loss of soil through erosion is a significant concern as it moves sediment and nutrients, leading to water pollution and eutrophication (Vanmaercke et al., 2021; Weil and Brady, 2017). Water erosion occurs through sheet (interrill), rill, and gully erosion processes (Poesen et al., 2003; Weil and Brady, 2017).

Soil erosion due to intensive use of marginal lands is a major problem that Haiti is facing (Jolly et al., 2007). Thus, the Environment Ministry of Haiti (MDE), in 2015, revealed that among all the types of degradation known in the country (salinization, erosion, nutrient depletion, etc.), erosion remains the most serious and widespread one. In recent years, the annual loss of land has been estimated to be 37 million metric tons (Bargout and Raizada, 2013; MDE, 2015). This amount corresponds to an average loss of 15 Mg/ha/year nationwide and is above the common tolerable threshold of 11 Mg/ha/year mentioned by Weil and Brady (2017).

Gully erosion is an important soil degradation process, as it can lead to soil losses of the same magnitude as those due to sheet and rill erosion (Boardman and Poesen, 2006). Gullies are natural channels that transfer runoff and sediment from higher to lower elevations (Poesen et al., 2003). Gullies differ from rills by a critical cross-sectional area of 929 cm² (Poesen and Govers, 1990). Gullies can have different cross-section shapes (V, U, trapezoidal) and can be classified based on their location as hillslope gullies, valley-bottom gullies, and field gullies (Thwaites et al., 2022). Permanent gullies are unaffected by regular tillage and persist in the landscape (Foster, 1986; Thwaites et al., 2022). Gully erosion is mainly induced by heavy rainfall events, but also depends on soil properties, geomorphological factors and land use and management (d'Oleire-Oltmanns et al., 2014).

In the Grande Rivière du Nord watershed in Haiti, gullies have a significant environmental impact, damaging infrastructure, filling reservoirs with sediment, and affecting agricultural areas. Gully erosion is an ongoing process in this watershed, necessitating the implementation

of measures to mitigate its effects and promote sustainable soil and water management practices. Remote sensing allows for accurate mapping and monitoring of gully erosion by providing high-resolution data over large areas. Prior to this research, no remote sensing studies had been carried out to assess gully erosion in the study area. The current research relied on Object-Based Image Analysis (OBIA) approach to automatically detect erosion in the specified watershed. This approach provides valuable insights into the extent of gully erosion in the Grande Rivière du Nord watershed, supporting the implementation of appropriate management strategies.

1.2. Research needs

Haiti is a mountainous country located in the Caribbean basin, sharing a large island with the Dominican Republic. It covers an area of 27,750 km² and has a rugged relief. The country, including its main islands, is divided into 30 watersheds. Unfortunately, 25 of these 30 watersheds are affected by severe degradation such as soil erosion, soil salinization, and nutrient and soil organic matter depletion (MDE, 2015). The ongoing deforestation remains the main cause of this degradation, as the forest ecosystem is decreasing by 2.5 ha per year. Additionally, erosive agricultural practices have led to a significant thinning of the surface layer of the soil. Soil erosion remains the most widespread form of degradation encountered in Haiti, due mainly to deforestation (Alscher, 2011; MDE, 2015).

This degradation is primarily caused by human activities and reflects deep-rooted socio-economic and institutional issues. Population growth, particularly in rural areas, has raised the demand for energy. Due to challenging socio-economic conditions, people rely heavily on charcoal as a source of energy for domestic and small-scale activities including baking, laundry, and distillery. A report from USAID (2007) highlights that 72% of Haiti's energy needs are met through local resources, namely fuelwood and charcoal (70%) and hydropower (2%). Additionally, certain farming practices such as sharecropping and short-term leasing do not incentivize farmers to implement long-term soil conservation measures (Jean-Denis et al., 2014). Since they are not landowners, farmers with these types of contracts tend to adopt short-term and erosive cultivation practices, neglecting the adoption of perennial vegetation systems that could contribute to erosion reduction. Moreover, the small size of agricultural plots, typically less than 2 hectares, hinders any sustainable land management efforts (Larose and Voltaire,

1984). These human-induced factors contribute to the ongoing deforestation in the region. The historical origins of deforestation date back to the 17th and 18th centuries, when colonial powers cleared forests to produce commercial crops and wood for export (Alscher, 2011; Hilaire, 1995). Furthermore, the structural crisis exacerbated by chronic political instability acts as an additional obstacle to technical progress and the implementation of sustainable land management practices.

As mentioned earlier, soil erosion is generally recognized as the dominant process of land degradation (Vanmaercke et al., 2021) and it's not different for the study area, largely affected by gully erosion. Gullies are vectors of water and sediment transmission in the downstream parts of the watersheds where the risk of flooding is the highest. Gullies represent a real issue and a serious challenge in the development of the territory in Haiti. Therefore, it is necessary to characterize them and map their extent in the landscape.

To reduce the consequences of gully erosion in Haiti, environmental programs have been implemented over the past two decades. These programs were designed to build physical and biological infrastructure for water and sediment retention and water infiltration in gullied areas in priority watersheds. To achieve the set objectives, the starting point for the implementation of watershed management projects consists in identification of gullies. However, the realization of the studies induces enormous costs in terms of time and money, and a high workload, since gully identification is done directly in the field by the staff. Hence, there's a need to propose to policy and decision makers a methodology for easily mapping the extent of gully erosion in Haiti. The use of object-based remote sensing analysis can provide an efficient and cost-effective solution to detect and monitor gully erosion in the Grande Rivière du Nord watershed in Haiti. And that perspective leads us to the following question: what is the performance of object-based remote sensing analysis to detect gully erosion in the context of the Grande Rivière du Nord watershed? The watershed of the Grande Rivière du Nord was chosen because it is one of the priority watersheds, characterized among other things by a high density of gullies, high soil erodibility and the vulnerability of the population and downstream infrastructures to natural disasters. The purpose of this work is therefore to provide stakeholders involved in watershed management with a new tool for erosion assessment that can precede any water and soil conservation strategy.

1.3. Objectives

The main objective of this research consists in assessing the performance of object-based image analysis to detect gully erosion in the Grande Rivière du Nord watershed. More specifically, this study aims to provide answers to specific questions:

- How accurate is the detection of gullied areas using high-resolution multispectral Pléiades imagery?
- What is the spatial extent of eroded areas in the Grande Rivière du Nord watershed?

1.4. Outlines of the thesis

This document materializes our research by grouping several parts organized into six chapters. The **first chapter** presents an overview of the study and highlights the needs that motivated our work. It also presents the pursued objectives and includes a summary of the different chapters at the end.

Chapter two, the literature review gathers research related to the current issue. **Chapter three** covers the methodology adopted to achieve the objectives. It presents the methods, materials, and tools used, starting from data acquisition to the performance assessment of the developed method. In this chapter, the potential use of Pléiades images for characterizing erosion in Haiti, particularly in the Grand Rivière du Nord basin, has also been investigated.

Chapter four emphasizes the results obtained by means of the methodology proposed in chapter three. The analysis of the results in **Chapter Five** enables a comprehensive discussion and contextualization of the findings in relation to existing studies focused on mapping gullied areas.

Finally, **chapter six**, the conclusion, summarizes the key results of the research, while presenting future improvement perspectives.

2. LITERATURE REVIEW

The first part of this chapter describes the erosion process and emphasizes its different forms (section 2.1). It primarily focuses on water erosion and specifically gully erosion, which is the key idea of this study. It then discusses the factors and consequences of water erosion in Haiti, concluding with a characterization of gully erosion on both a national and global scale. The following two sections (2.2 and 2.3) present the methods used in the study and mapping of gully erosion, including field surveys and remote sensing techniques such as aerial photography and image analysis. The subsequent section (2.4) highlights the benefits of combining artificial intelligence with the two approaches to remote sensing image analysis (pixel-based and object-based). Finally, the last section (2.5) provides a summary of this chapter, recapping the key elements discussed.

2.1. Soil erosion process

2.1.1. Definition and factors

The term "erosion" refers to the process of detachment and transport of solid particles from the soil, primarily caused by natural forces such as water and wind (White, 2006). When the energy for particle transport decreases, deposition occurs as a third phase (Morgan, 2009; Weil and Brady, 2017). Apart from water and wind, erosion can also be induced by other factors such as tillage, harvesting, and gravity in the case of landslides (Blume et al., 2016; Boardman and Poesen, 2006; Weil and Brady, 2017).

Soil erosion is a significant hazard commonly associated with agriculture in tropical and semi-arid regions, and it has long-term implications for soil productivity and sustainable farming practices. Additionally, erosion contributes to environmental damage through sedimentation, pollution, and increased flood risk. These negative impacts occur both on-site and off-site, resulting in substantial costs (Morgan, 2009). According to Weil and Brady (2017), agricultural soil erosion globally leads to annual economic impacts exceeding \$500 billion when considering both on-site and off-site effects.

2.1.2. Water erosion

Erosion by rainfall is a natural geomorphological process (Gafurov and Yermolayev, 2020; Shahabi et al., 2019). It is controlled by a set of factors including topography, climate, soil type and vegetation (Boardman and Poesen, 2006; Morgan, 2009; Poesen et al., 2003). However, water erosion can be accelerated by human activities and have negative effects on agriculture, land, and infrastructure (Morgan, 2009; Vanmaercke et al., 2021). Water erosion is widespread in arid regions where vegetation is sparse and rainfall is occasionally heavy (Blume et al., 2016).

According to Weil and Brady (2017), three types of water erosion are generally recognized: (1) sheet, (2) rill, and (3) gully erosion. Additionally, other forms of water erosion occur, such as bank erosion in rivers, erosion in glaciated areas (Boardman and Poesen, 2006), and piping or tunnel erosion (Blume et al., 2016; Kariminejad et al., 2023; Morgan, 2009; Weil and Brady, 2017). Sheet erosion refers to the relatively uniform erosion that occurs across the entire soil surface. When sheet erosion occurs between irregularly spaced rills, it is referred to as interrill erosion (Foster, 1986; Weil and Brady, 2017). Rill erosion, on the other hand, occurs when water concentrates in small channels known as rills as it flows over the soil. Although subsequent cultivation may remove rills, it does not replace the eroded soil. Rills are channels that are small enough to be smoothed by regular tillage practices, but they still result in soil loss (Weil and Brady, 2017). Gullies are effective linkages for transferring runoff and sediment from uplands to valley-bottoms and permanent channels where they compound the off-site effects of water erosion (Poesen et al., 2003). Sections 2.1.3 and 2.1.4 are devoted to characterizing this form of water erosion.

According to Blume et al. (2016) and Weil and Brady (2017), sheet or diffuse erosion and rill erosion are considered important due to the large volume of soil they can mobilize. These forms of erosion occur over a relatively broad area and can contribute to the overall sediment load in a watershed. However, Valentin et al. (2005) insisted that gully erosion is the most severe form of water erosion. Indeed, gully erosion refers to the formation of deep channels in the landscape, which can lead to significant soil loss and landscape degradation. In line with this, Vanmaercke et al. (2021) stated that gullies can also be a major source of sediment. Their high erosion rates make them significant contributors to sediment yield in catchments. In some cases, gullies can account for a substantial proportion, ranging from 20% to 80% of the total sediment yield from a catchment.

Different mechanisms of detachment and transport occur depending on whether it is rill/gully erosion or interrill erosion. In interrill erosion, detachment primarily happens through splash, which is caused by the impact of raindrops on the soil surface (Morgan, 2009). Additionally, soil wetting processes including dispersion of aggregates, rapid swelling, air compression, and slaking have uniform effect in unprotected soil (Blume et al., 2016). Both the drops and the runoff are involved in the transport of the loose particles. On steep slopes, splash plays a significant role in transporting soil particles in the interrill areas. However, in rills and gullies, detachment, and transport (by bedload and suspension) are exclusively driven by the force of runoff water (Blume et al., 2016; Morgan, 2009).

Figure 2.1 (a) shows a raindrop speeding towards the ground, (b) is the resulting splash when the drop strikes a wet and bare soil and (c) detached soil particles, which are then transported and eventually deposited when energy is insufficient to ensure transportation particularly in lower elevation (Morgan, 2009; Weil and Brady, 2017).

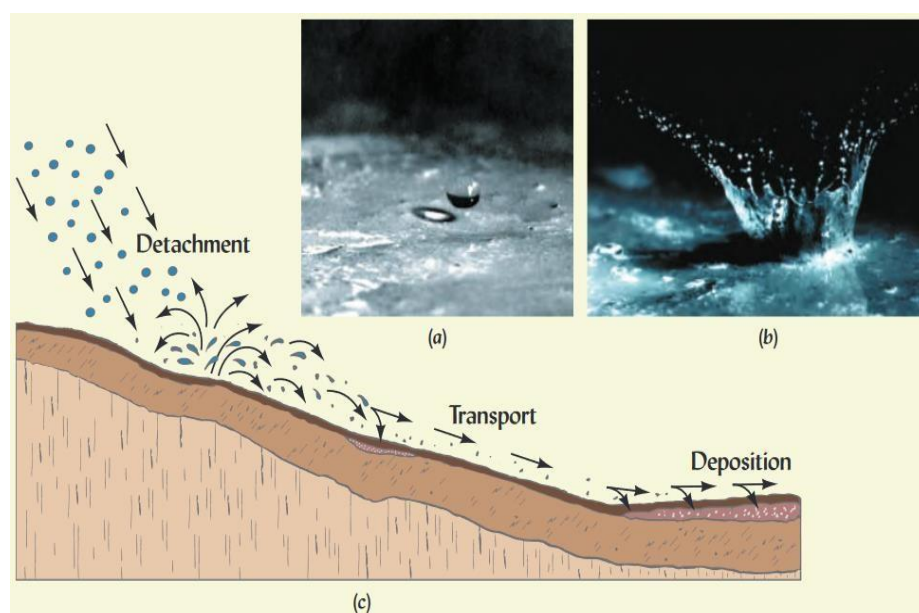


Figure 2.1: The three-phase process of water erosion (Weil and Brady, 2017) which consists of the detachment, transport and deposition of soil particles

2.1.3. Gully erosion background

If the rills get deeper, so that they can no longer be crossed by farm machinery and thus removed by soil tillage, it is referred to as gully erosion (Blume et al., 2016; White, 2006). Rills differ

from gullies in size, and the critical area of 929 cm² (0.3 m wide x 0.3 m deep) was defined as the boundary between them (Morgan, 2009; Poesen and Govers, 1990). No upper limit has been clearly defined yet for gullies and the limit between large gully and river channel remains blurred (Poesen et al., 2003; Vanmaercke et al., 2021).

Gullies on cropland are obstacles for tractors and cannot be removed by ordinary tillage practices (Weil et Brady, 2017). Gully erosion is mainly induced by heavy rainfall events, but also depends on soil properties, geomorphological factors and land-use and management (d'Oleire-Oltmanns et al., 2014).

2.1.4. Gully characterization

To date, most research dealing with soil erosion by water has focused on sheet (interrill) and rill erosion processes operating at the plot scale (Vanmaercke et al., 2021). Relatively few studies have been conducted on gully erosion involving larger spatial scales (Poesen et al., 2003). In the current century, the importance of gully erosion has attracted a lot of attention, with an increase in publications relating to its initiation, control factors and adverse effects. Parameters such as gully size, shape and distribution can provide basic information for determining the rate of gully erosion and predicting its development (Liu et al., 2018). In this respect, Valentin et al. (2005), Li et al. (2017), and Shahabi et al. (2019) claimed that gully erosion is a threshold-dependent process controlled by a wide range of factors such as topographic threshold (slope gradient and drainage area), geomorphology and soil crusting.

The literature provides a substantial number of different approaches for classification of gullies. They can be classified according to:

- The shape of their cross section in V, U and trapezoidal
- Their domain in ephemeral, classic or permanent, alluvial, upland
- Their family in field gully and landscape gully

Boardman and Poesen (2006) cited special studies that classified gully erosion into three categories based on gully length density:

- Weakly gullied area: gully length density less than 200 m km⁻²
- Moderate gully area: gully length density between 200 and 500 m km⁻²

- Severely gullied area: gully length density greater than 500 m km⁻²

However, Vanmaercke et al. (2021) argued that gully length density alone is insufficient to assess the severity of gully erosion. Morgan (2009) and Vanmaercke et al. (2021) stated that it is important to also consider the rate of gully expansion, infrastructure damage, and the costs involved in repairing the damage. Vanmaercke et al. (2021) added that factors such as gully width, cross-sectional area, and total gully volume are often of interest when assessing gully erosion.

2.1.5. An overview of soil erosion in Haiti

Soil erosion due to intensive use of marginal lands is a major problem that Haiti is facing (Jolly et al., 2007). The Environment Ministry of Haiti, in 2015, revealed that among all the types of degradation known in the country (salinization, erosion, nutrient depletion, etc.), erosion remains the most serious and widespread one. This institution argued that erosion has removed an average of 3 cm of fertile land over the past five decades. The annual loss caused by water erosion was estimated to be 7 million metric tons in late 1930s (Bargout and Raizada, 2013). In recent years, the annual loss of land increased to 37 million metric tons (MDE, 2015). This amount corresponds to an average loss of 15 Mg/ha/year nationwide and is above the common tolerable threshold of 11 Mg/ha/year mentioned by Weil and Brady (2017).

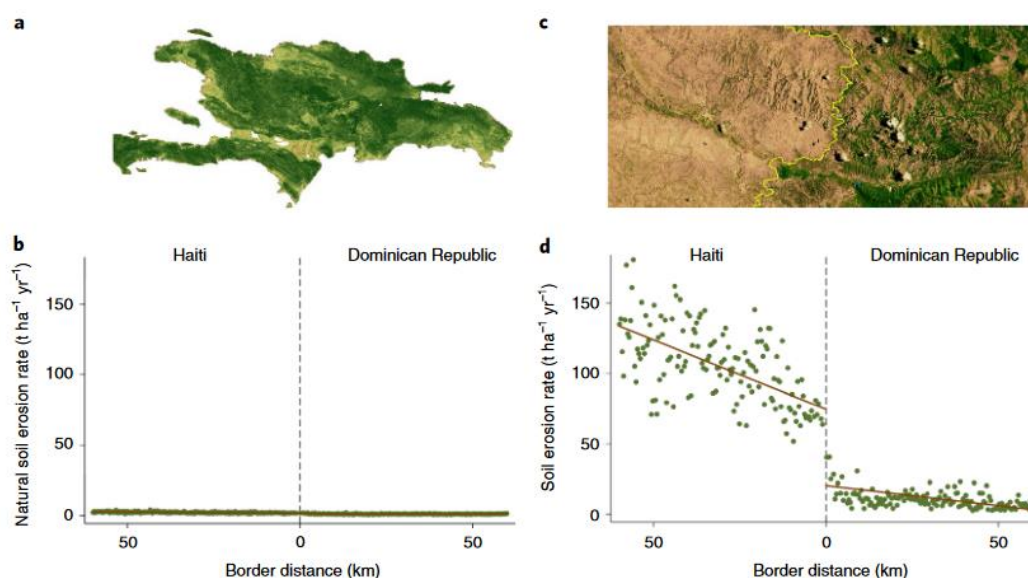


Figure 2.2: Comparison of soil erosion on either side of the border between Haiti and the Dominican Republic (Wuepper et al., 2019)

In Haiti, soil erosion is influenced by both intrinsic biophysical and anthropogenic factors (Bargout and Raizada, 2013). To gain a deeper understanding of the underlying cause of erosion in the country, the study conducted by Wuepper et al. (2019) provides valuable insights. The researchers modeled erosion along a 17 km stretch on either side of the border between Haiti and the Dominican Republic. Biophysical factors, such as topography, rainfall, soil, and vegetation, were similar for both countries at the border. The study found that in the absence of human intervention (figure 2.2 a), the island of Hispaniola would have had a uniform natural soil cover dominated by forests (figure 2.2 b). The potential natural rate of soil erosion was projected to be low and evenly distributed across the border. However, a distinct disparity in actual soil cover was observed between the two countries (figure 2.2 c), primarily due to contrasting historical deforestation rates. Notably, the actual soil erosion rate was significantly higher than the potential natural rate (figure 2.2 d). The researchers concluded that the observed erosion discontinuity is a result of human activities and their impact on the landscape. This finding is consistent with the results obtained by Borrelli et al. (2017), who also emphasized the role of land use and management in driving accelerated soil erosion. These studies contribute to a global understanding of soil erosion processes, but they specifically highlight Haiti as a country highly susceptible to water erosion, emphasizing the importance of land use practices in influencing erosion rates.

Additionally, biophysical factors such as relief, parent material, and climate exacerbate water erosion in Haiti. Among these factors, topography is the most significant contributor to soil erosion. According to the Ministry of Environment (MDE, 2015), only 20% of the land in Haiti has a slope less than 10%, while more than 60% of the land has a slope gradient exceeding 20%. This steep terrain and mountainous landscape make gully erosion more prevalent than rill and interrill erosion in Haiti (El-Swaify, 1997). Furthermore, the presence of gullies increases the risk of flooding. Therefore, effective measures for gully control and rehabilitation need to consider the dynamics and extent of gullies over time (Daba et al., 2003).

2.1.6. Gully erosion in Haiti

Boardman and Poesen (2006) categorized contemporary gullies into two groups based on their location within a catchment. The first group consists of gullies found on the slopes of valley and agricultural plots (called hillslope gullies). The second group comprises valley-bottom gullies, which are characterized by their substantial length, drainage area, and low longitudinal

gradient, as illustrated in Figure 2.3 . In Haiti, these two types of gullies are part of a broader classification:

- Historic gullies which are related to the relief (valley-bottom gullies). In urban areas, they often serve as natural drainage channels.
- Gullies developed on slopes (or resulting from landslides) due to desertification, soil instability, heavy rainfall, and high slopes. These gullies evolve more rapidly than the previous ones.
- Ephemeral gullies that form on plots or along dirt roads during the rainy season.

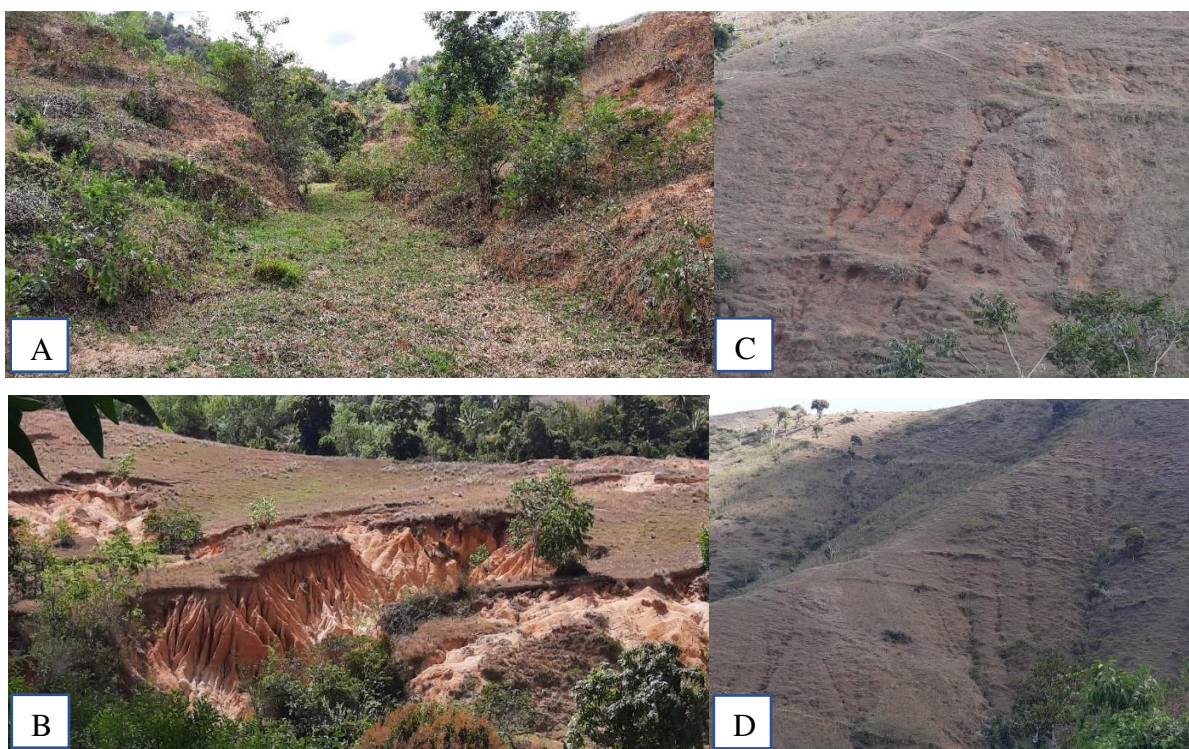


Figure 2.3: Illustration of a large valley-bottom gully (A), a gully developed in fields and on intermediate slopes (B), a system of rills and deep gullies on steep slopes (C and D)

Valley-bottom gullies exhibit base widths up to nearly 20 meters. These gullies have a distinctive V and trapezoidal shape, with contrasting widths between the bottom and top surface. They can be either bare or vegetated and are present across a wide range of slopes, with either no flow or temporary flow. Locally, a common practice is to use a base width threshold of 3 meters for large gullies (called ravines in some studies). However, some research compiled by Thwaites et al. (2022) suggested using depth as the criterion for differentiating gullies from

ravines. According to their findings, gullies with a depth exceeding 5 to 10 meters are classified as ravines (large gullies).

Hillslope gullies, which are permanent and unaffected by regular tillage, present greater challenges than ephemeral gullies in cultivated land as they are a continuous erosion process. They are characterized by narrow width relative to their depth, steep sidewalls, and prominent terminal heads (Foster, 1986). These types of gullies are particularly challenging in Haiti.

2.2. Field survey in gully erosion characterization

According to Nachtergaele and Poesen (1999), the most reliable method for collecting gully erosion data is to conduct field visits following rainfall events. Similarly, Liu et al. (2017) emphasized that field assessment is the most traditional and direct method to obtain gully information. However, this method has limitations in terms of spatial coverage and cost (Liu et al., 2018; Nachtergaele and Poesen, 1999).

With the increasing trend of technological advancements in surveying and gully mapping, several techniques have been proposed regarding erosion detection and assessment (Castillo et al., 2012). Erosion from relatively small gullies can be assessed using the profiling technique which consists of transect across the slope to determine the cross-section area. However, for larger gullies, sequential surveys using aerial photography have been found to be more appropriate (Morgan, 2009). Castillo et al. (2012) used ground-based LiDAR (Light Detection and Ranging), 3D photo-reconstruction, laser profile-meter, and total station with the advantages of high precision and low cost. However, the cumbersome fieldwork associated with these technologies limits their application to a small-scale study, according to Liu et al. (2017). In this context, remote sensing in soil research can serve as a substitute for direct field data collection and enhance data availability (Castillo et al., 2012; Liu et al., 2017).

2.3. Remote sensing approaches in gully mapping

2.3.1. Aerial photography

Visual interpretation of aerial photographs was developed in the 1940s as a useful method of obtaining information about gullies (Liu et al., 2017). Until recently, this reflectance-based

approach had been the primary method for gully extraction (Shruthi et al., 2011). Nachtergaele and Poesen (1999) conducted a study using aerial photographs to evaluate soil loss caused by ephemeral gully erosion. Their findings demonstrated that the results were consistent with other research methods employed to assess soil loss resulting from ephemeral gully erosion in the Belgian loess belt. Later, Daba et al. (2003) used photogrammetric techniques to assess gully erosion in eastern Ethiopia. More recently, Maignard et al. (2014) have processed uncertainty assessment of ephemeral gully identification when using aerial photographs in agricultural settings. They noted that operator subjectivity during digitization of gullies on orthophotos introduced uncertainty, which should be considered in future remote sensing-based studies on gully erosion. Their results indicated that 34% of the gullies were digitized by more than half of the operators, while only 7% were identified by all.

Aerial photograph, often combined with photogrammetric techniques, had been used for long (Daba et al., 2003; Nachtergaele and Poesen, 1999), but Liu et al. (2017) argued that its low efficiency has led researchers to explore automatic methods. On the other hand, Shruthi et al. (2014) revealed that visual assessment methods are inefficient and subjective when applied to large areas.

2.3.2. Satellite imagery

The launch of Landsat spatial mission in 1972 made satellite imagery available to the scientific community (Liu et al., 2017; Shruthi et al., 2011). These images facilitated successful visual analysis of ravine areas at a small scale (Singh, 1977). Years later SPOT and IKONOS satellites provided researchers with high-resolution multi-temporal satellite imagery (Mohamadi et al., 2021; Morgan, 2009; Vrieling et al., 2007; Yan et al., 2006). This availability of satellite images led to the development of new approaches for studying gully processes worldwide. Two prominent approaches in image analysis emerged: Pixel-based Image Analysis and Object-based image analysis.

2.3.2.1. Pixel-based image analysis

The contribution of remote sensing to the spatial assessment of gullies had long been limited to the interpretation of visual images (Vrieling et al., 2007), but the size of studied region was relatively small. Yan et al. (2006) recommended the use of automated method like Pixel-based Image Analysis (PIXA) to automatically extract gullies due to the low efficiency of the visual

interpretation. With this method, each pixel of the image is analyzed separately based on its surface reflectance, then automatic extraction of the gullies is performed (Shruthi et al., 2011; Vrieling et al., 2007).

However, the accuracy of this method is limited using spectral information only, after Karami et al. (2015). Thus, no other image-related information such as spatial and textural context is considered (Blaschke, 2010). In traditional pixel-based approach, the result of landform analysis completely relies on individual pixel information (Vrieling et al., 2007), using specific algorithms and techniques to extract information and perform tasks such as classification, segmentation, and object detection. In addition, the spectral variability associated with gully characteristics, such as the presence of vegetation or differences in brightness related to shade or moisture, cannot be effectively captured with a method based purely on spectral information (Shruthi et al., 2011).

2.3.2.2. *Object-based image analysis*

With the ever-increasing availability of high-resolution imagery, it became possible to dispense with traditional pixel-based methods. Object or feature analysis, as opposed to individual pixels, is more appropriate for dealing with heterogeneity, and more suitable for knowledge-based analysis such as visual image interpretation (Shruthi et al., 2011). In addition to the spectral description of objects, OBIA method provides additional spatial information like spatial topology, geometric descriptions (shape, texture), etc. (Blaschke, 2010; Mohamadi et al., 2021; Shruthi et al., 2011). In contrast to the typical Landsat resolution, high-resolution images can support multiple scales in their images (Blaschke, 2010).

During the last two decades, researchers have used object-based methods for gully extraction, characterization, classification, and mapping (Blaschke, 2010; d'Oleire-Oltmanns et al., 2014; Karami et al., 2015; Mohamadi et al., 2021; Shahabi et al., 2019; Vrieling et al., 2007). Others have compared this method to the traditional pixel-based method, as well as to previous methods devoted to the study of gullies (Castillo et al., 2012; Yan et al., 2006). Some of them have found that pixel-based classification often leads to the well-known "salt and pepper" effect, where individual pixels are classified differently from their surrounding areas, resulting in a lack of homogeneous regions (Blaschke et al., 2000). To smooth an image, filters can be applied, but they do not consider the original information. In contrast, classification based on segmented images can reduce the salt and pepper effect (Blaschke et al., 2000; Karami et al.,

2015; Mohamadi et al., 2021) without the need for additional filtering operations. This approach involves building up homogeneous regions or image objects first and then applying classification to these objects (Blaschke et al., 2000).

However, it is worth noting that reducing the salt and pepper effect is not always advantageous. While OBIA approach effectively reduces this effect by merging pixels into objects and small objects into larger ones, it may also result in the loss of important detail information during this process (Karami et al., 2015).

Moreover, researchers have sought to enhance the results obtained from PIXA and OBIA by combining them with artificial intelligence (AI) methods. By integrating AI techniques, such as machine learning algorithms, researchers aim to leverage the strengths of PIXA and OBIA while benefiting from the advanced learning and pattern recognition capabilities offered by AI. This combination has the potential to improve the accuracy and efficiency of image analysis tasks, including classification and segmentation, by leveraging the complementary features of these approaches (Azeez et al., 2022).

2.4. Deep learning approach in gully mapping

2.4.1. Background

Deep learning is a subset of machine learning (Goodfellow et al., 2016, Trimble, 2023) that utilizes artificial neural networks to analyze data. Deep learning approach and architectures were inspired by insights into the functioning of the nervous system and mimics human perception. It does not require human-designed rules to operate (Alzubaidi et al., 2021; Trimble, 2023). Instead, it uses a large amount of data to map a given input to specific labels. Artificial neural networks, which are composed of numerous layers of algorithms, provide different interpretations of the input data (Alzubaidi et al., 2021). Machine learning, on the other hand, is a specialized field within the broader framework of artificial intelligence. It encompasses a series of approaches that allow systems to automatically improve their performance and gain knowledge through experience, without requiring explicit programming (Trimble, 2023).

One popular type of deep learning architecture is the Convolutional Neural Network (CNN), which is easy to train. CNNs are often used in many applications of deep learning, including

video recognition, image analysis, natural language processing, and more (LeCun et al., 2015; Salehi et al., 2017). Convolutional neural networks have become increasingly popular due to their ability to process data efficiently and accurately with a grid-like structure (Goodfellow et al., 2016) such as images and videos. The use of convolutions instead of matrix multiplication allows for more efficient processing of large datasets, making CNNs ideal for tasks such as image and video recognition, as well as other applications like financial time-series analysis (Parveez and Iriondo, 2021).

With the effect of so-called convolutional layers and pooling layers, CNNs can extract input image features more efficiently than traditional feedforward neural networks with inductive bias introduced by convolutional kernels (Liu et al., 2023). In recent years, some researchers have experimented the use of neural networks in gully detection. As example, Gafurov and Yermolayev (2020) tested an approach based on the use of convolutional neural networks for automated gully detection on the RGB-synthesis of ultra-high resolution satellite images, while Liu et al. (2022) used deep learning in the hilly and gully region of the Loess Plateau in China for ephemeral gully recognition. Both studies found that deep learning, particularly convolutional neural networks, can accurately process large amount of data to recognize gullies in remote sensing images. However, this is an emerging approach, still being studied in the context of gully mapping.

2.4.2. CNN architecture

Convolutional Neural Networks (CNNs) are particularly useful in image analysis. They refer to a class of neural network models with convolutional structures, according to Liu et al. (2023). CNN is mainly composed of several different types of layers including input layer, hidden layer, fully connected layer, and output layer (Figure 2.5). The CNN architecture has two distinct layers in each hidden layer: a convolutional layer consisting of kernels and a pooling layer.

A kernel consists in a small matrix used for the convolution operation in a CNN (Figure 2.4). It is usually a square matrix that contains numerical values called weights (LeCun et al., 2015). The kernel is applied to the input image by a convolution operation to produce a feature map (Trimble, 2023). It works by sliding a set of filters over the input image (Figure 2.5), performing the convolution operation between the filter and the input at each position, and producing a

feature map that highlights important patterns in the image. Each kernel is designed to detect specific patterns or features in the input data.

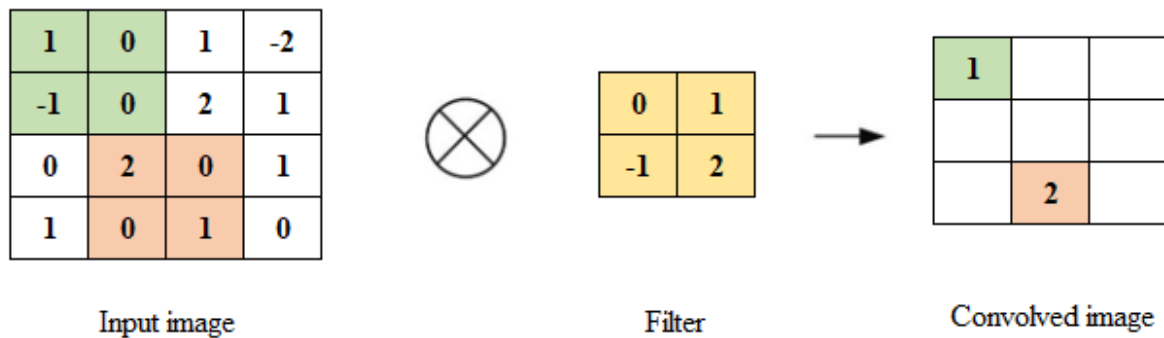


Figure 2.4: Illustration of two steps of a convolutional operation performing element-wise multiplication between the kernel weights (filter) and the input values (1 channel) within the receptive field, and summing the result (convolved image)

Each layer of a CNN model has three dimensions: height, width, and depth, and the input is organized in a tensor with dimensions $m \times m \times r$, where the depth also refers to as the channel number. After several hidden layers, the final layer is typically a fully connected layer. Down-sampling or pooling layers reduces the network parameters, accelerates the training process, and helps handle overfitting issues (Alzubaidi et al., 2021).

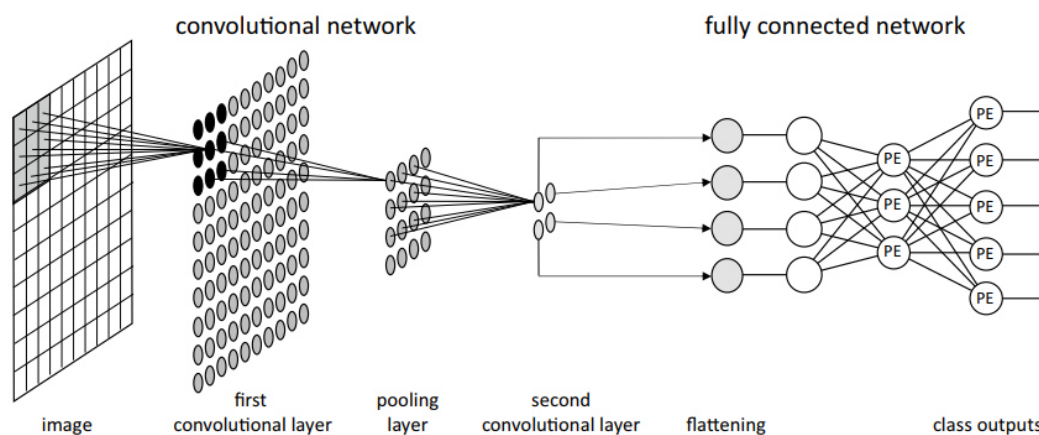


Figure 2.5: An example of CNN architecture for image classification (Richard, 2022)

2.4.3. Integration of CNNs and remote sensing data

Convolutional neural networks have demonstrated superior performance in various computer vision and pattern recognition tasks (Azeez et al., 2022; Gafurov and Yermolayev, 2020). CNNs excel at automatically learning visual features from large image datasets, leading to significant improvements in image classification and segmentation capabilities. They can be applied to both pixel-based and object-based image analysis.

While CNNs are proficient at extracting visual features, pixel-based classification solely using CNNs may not effectively capture spatial and contextual relationships among image pixels. This can result in redundant computations and low performance (Azeez et al., 2022). To overcome this limitation, researchers have explored the combination of CNNs and OBIA approaches. In the study conducted by Azeez et al. (2022) on image classification of high-resolution aerial photographs, four common frameworks for combining CNNs and OBIA were compared. The study found that incorporating OBIA improved the classification performance when using CNNs.

2.5. Summary of the literature review

If sheet and rill erosion can easily be estimated from empirical models such as the Universal Soil Loss Equation (USLE) and its derivatives like MUSLE and RUSLE, gully erosion is still under the spotlight of researchers. This form of water erosion attracts their attention since water plays a double role of uprooting and transporting soil particles. Indeed, gully mapping can provide land managers and policymakers with a better understanding of gully erosion (Liu et al. 2018) and help them in improving water and soil conservation strategies.

In the past, gullying had been detected directly in the field, but this method is expensive. It requires a huge workload for a low efficiency. However, direct measurements in the field are still used as a reference for the validation of other methods. Aerial photography has, for a long time, experienced a lightning ascent, given its applicability on a larger scale. Often associated with photogrammetry, it is unfortunately subject to the sensitivity of the expert, especially during the digitization process. Secondly, aerial photography missions are often punctual and do not favor the monitoring of an environmental process. With the availability of satellite images such as Landsat, Quickbird, ASTER, to name but a few, other detection methods have

emerged. Pixel-based and object-oriented image analysis were developed at the dawn of the 21st century by researchers. And in the past decade, the OBIA method has become a reference in large-scale gully detection and classification. In addition, the continuous improvement of spatial resolution facilitates the integration of data derived from Digital Terrain Model (DTM) like Stream Power Index (SPI), elevation, and slope to refine the detection process.

Studies in Haiti have mainly focused on the factors of soil erosion (Dolisca et al., 2009; Williams, 2011) rather than its measurement or extent, where manual methods are still the norm for gully detection. No remote sensing-based detection methods have been identified to date to study gully erosion in the Grande Rivière du Nord watershed in Haiti. Nonetheless, given the geomorphology of the country as a flood's co-driver, considering its location in the tropical zone and, given the pressures on the land due to the socio-economic situation, mapping the extent of gully erosion is fundamental. Within the framework of this research, the OBIA method is targeted as the basis for detection, with an insight to the reproducibility of the method to other areas of the country. This digital solution was coupled with a field survey to assess the accuracy of the used method.

3. MATERIALS AND METHODS

3.1. Study area and data source

3.1.1. Description of the study area

Chosen to host this research, Haiti is a country located in the Caribbean region, sharing a large island with the Dominican Republic. Its geography is characterized by a mountainous topography, which results in significant climatic variations across the territory, even within regions just a few kilometers apart. The country falls under the subtropical lowland region, with a latitude range of 18° to 20° north. The climate in the plains and low mountain areas is typically a tropical monsoon, characterized by high temperatures and heavy rainfall during the summer months, with a dry season from November to March (GRET and FAMV, 1990). In contrast, high altitude areas experience subtropical climate with cooler temperatures and even more rainfall (MDE, 2015).

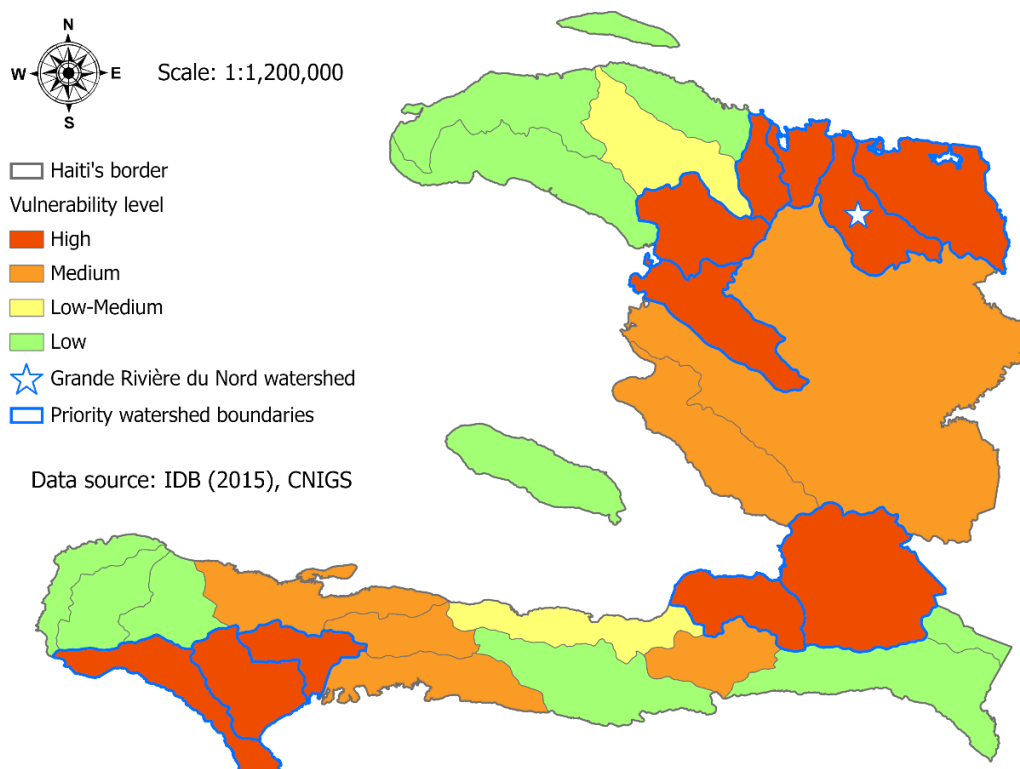


Figure 3.1: A composite map based on median value of population and infrastructure vulnerability to natural disasters, and soil potential at watershed level

Figure 3.1 is a composite map based on the median value of five indices: the vulnerability of the population and infrastructure (roads, markets, irrigation systems) to natural disaster risks, and soil potential at the watershed level. The most significant risk identified in the composite map is flooding, which is closely associated with the frequency of major climatic events, particularly tropical cyclones. This composite map was based on data from the United States Agency for International Development (USAID, 2007). The prioritized watersheds identified in the map are those that exhibit the highest level of vulnerability, as determined by the Inter-American Development Bank (IDB, 2015). The map has served as a tool to identify and prioritize areas that required targeted interventions and resources to mitigate the impacts of natural disasters on the local population and infrastructure.

The Grande Rivière du Nord watershed has been selected as the study site due to its designation as a priority watershed (Figure 3.1), at high risk of soil erosion. The topography of the region is marked by a sequence of hills that form an undulating landscape, with an average slope of 25%. The watershed is located between parallels 19°23' and 19°46' North latitude and meridians 71°53' and 72°13' West longitude and covers an area of 680 km².

The study site receives significant amounts of rainfall, with over 60% of the watershed receiving more than 1500 mm annually, and up to 2,300 mm in mountainous areas (MARNDR et al., 2011). The average monthly temperature ranges from 24°C to 27.6°C throughout the year. According to data from CNIGS, the study area is composed of two main types of parent materials: magmatic rocks and sedimentary rocks. Magmatic rocks such as diorites, andesites, rhyodacites, and sedimentary rocks like marl, sandstone, marly limestone, detrital materials, and alluvium are common in the region. On steep hillsides, soils derived from most of these materials are highly prone to erosion in Haiti (GRET and FAMV, 1990).

Furthermore, the lack of vegetation cover exacerbates the erosion process, resulting in the prevalence of gullies in the field. The presence of these soil types and geomorphology, along with other contributing factors, underscores the relevance of studying erosion process in the study area.

3.1.2. Justification of the study area

In the Grande Rivière du Nord watershed, the municipality of Sainte-Suzanne (Annex E) was chosen as the focal point for the methodology development due to several key factors. Firstly, its ecosystems accurately represent the overall characteristics of the watershed, particularly in term of relief and soils. This ensures that the findings and conclusions drawn from the study in Sainte-Suzanne can be effectively applied to the entire watershed. Secondly, Sainte-Suzanne stands out as the major contributor to the flow of the Grande Rivière du Nord, as all the water from the municipality is drained into its main river. Additionally, Sainte-Suzanne was identified as highly susceptible to water erosion, making it an ideal location for studying and implementing erosion control measures. Lastly, the decision to select Sainte-Suzanne was influenced by the challenging security situation prevailing across the country at the time of the field visit. Considering the safety concerns, Sainte-Suzanne was regarded as a comparatively low-risk zone, allowing for more feasible and secure fieldwork.

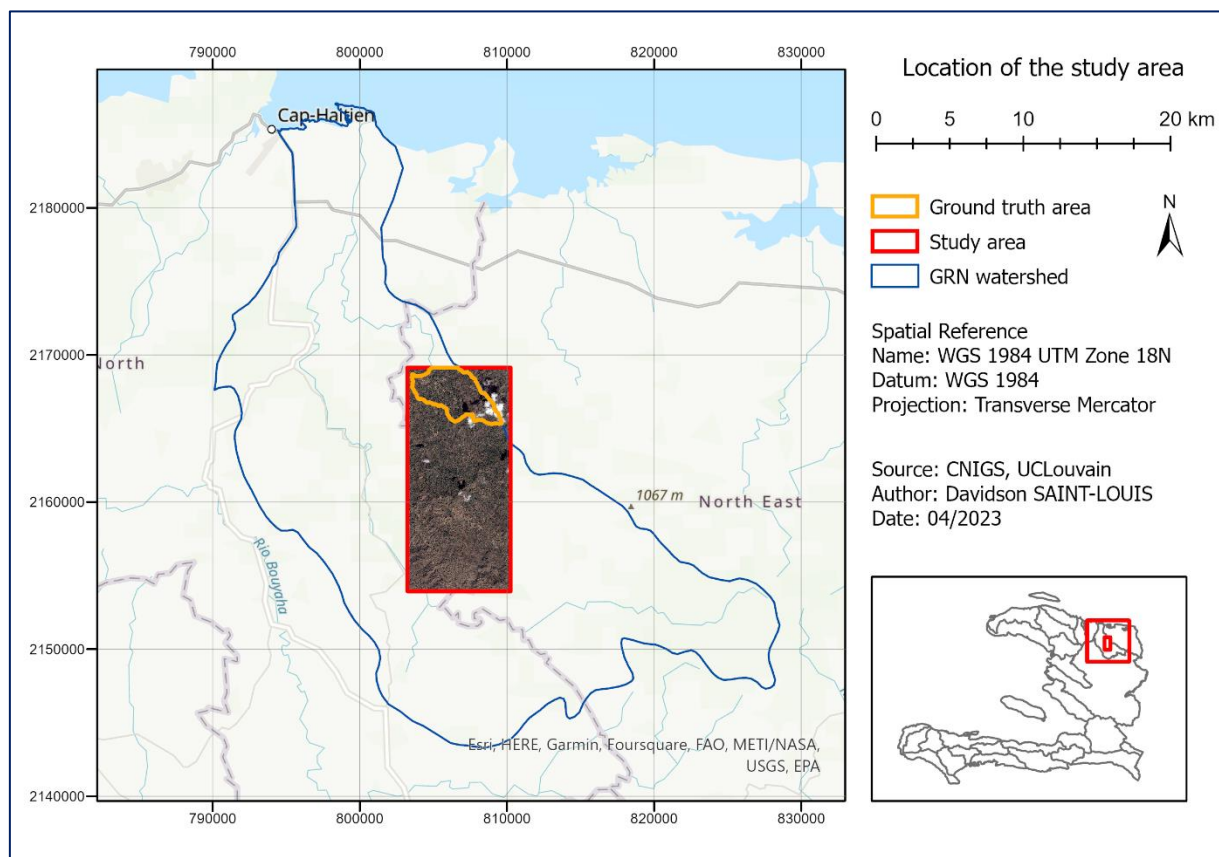


Figure 3.2: Location of the study area within the Grande Rivière du Nord watershed

Figure 3.2 shows the orthorectified image scene from the Pléiades satellite, which overlays the study area within the watershed. The study area covers an area of 106 km², approximately one-sixth of the total watershed area of 680 km². The ground truth area for validation purposes is 13.80 km². The validation data for gully-affected areas were collected within this zone (in point shape format). This area was arbitrarily chosen based on interpretations of aerial photographs that revealed potentially eroded sites, which were indeed confirmed during the study.

3.1.3. Source of the remote sensing data

This study combines data from two main sources: the Centre National de l'Information Géospatiale (CNIGS), a national Haitian Institution, and Airbus Defence and Space (ADS). The CNIGS provided mosaicked satellite images with a 25 cm resolution and a Digital Elevation Model (DEM) with a 1.5-meter resolution acquired through aerial photography between 2014 and 2016. On the other hand, ADS provided Pléiades satellite images acquired on March 16, 2023, consisting of three multispectral and panchromatic scenes with a 2-meter resolution for multispectral imagery and 50 cm for panchromatic imagery (Table 3.1). The capture area covered a 106 km² rectangle corresponding to the study site, with the images carefully selected to minimize cloud cover and their shadows. However, a significant portion of these images was affected by clouds, limiting their use for this study.

Table 3.1: Comparison between CNIGS and Pléiades imagery

Source	Airbus DS	CNIGS
Satellite	Pléiades	-
Product resolution	Panchromatic 0.50 m Raw multispectral and orthophoto (2 m)	0.25 m color
Spectral bands combination	PAN + 4-band MS	3 bands (RGB)
Image format	NITF (2) – GeoTIFF(1)	GRID Stack 7.x
Bit depth	12 bits (1)	8 bits
Wavelength	Pan: 470 – 830 nm Blue: 430 – 550 nm Green: 500 – 620 nm Red: 590 – 710 nm NIR: 740 – 940 nm	-

Despite this limitation, the potential of these images has been demonstrated for different uses such as environmental monitoring, land-use and land-cover classification, and disaster response. Additionally, Airbus provided a 2-meter resolution orthophoto a few days later, which was combined with the corresponding panchromatic image to generate a high-resolution DEM. The combination of Pléiades and CNIGS images allowed for a better understanding of the study area's environmental conditions and the identification of gully patterns. These images are captured within a wavelength range of 430 nm to 940 nm, which includes a large portion of the visible spectrum (400 – 700 nm) and a small portion of the near infrared.

3.1.4. Terrain data

Prior to the field survey in February 2023, the study area was screened using Google Earth and CNIGS aerial images from 2016. A planned transect in the municipality of Sainte-Suzanne enabled the identification of a potential gully zone, which was essential for collecting validation data. Due to the high density of gullies and the extent of gully-affected areas, the goal was not to systematically sample all gullies within the area visited, but to obtain accurate ground truth data for a true and independent accuracy assessment following the classification step.

For validation purposes, two sub-basins were initially selected, which exhibited significant variations in vegetation cover, slope, land use, and soil type. Due to cloud cover, only the final subset of 13.80 km² has been considered for the ground truth area.

3.2. Methodology Workflow

The methodology workflow provides a comprehensive overview of all the steps involved in this study, with a focus on five main stages:

- Data acquisition through both fieldwork and remote sensing
- Data preprocessing
- Segmentation of the acquired data
- Classification of the segmented data (objects)
- Evaluation of detection performance

Figure 3.3 shows the overall methodology adopted through the study.

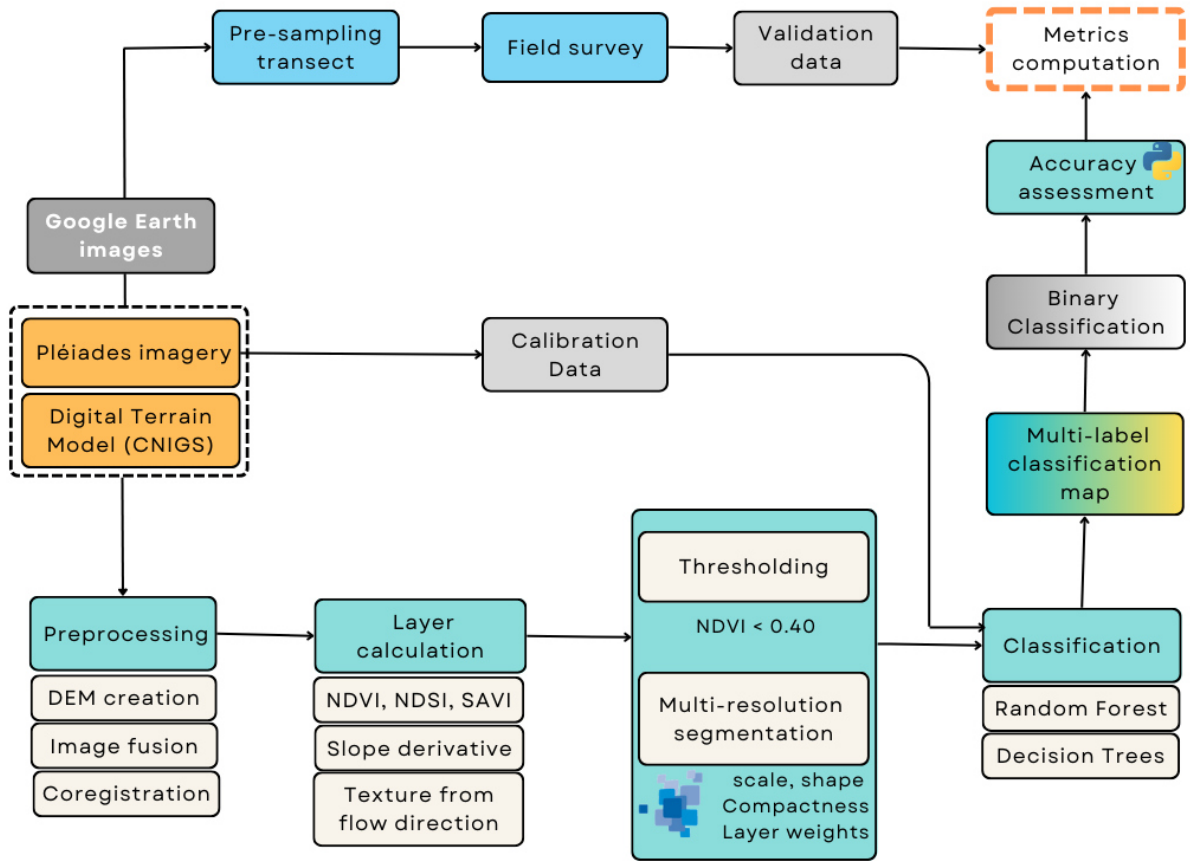


Figure 3.3: Overall proposed workflow of the study

3.3. Remote sensing data preparation

Remote sensing data preparation is an essential step in many environmental studies, including the detection and monitoring of gully erosion. In this study, elevation data and high-resolution images were necessary to accurately delineate gully-affected areas and enhance segmentation. To generate a Digital Elevation Model (DEM), three scenes of Pléiades images were processed. Additionally, pan sharpening, a technique for increasing the spatial resolution of a multiband image, was used to create high-resolution, updated images for synchronization with the field survey. The following sections describe the process of DEM creation and image fusion in detail.

3.3.1. DEM generation

Elevation data are essential to improve object delineation during the image segmentation process. For this purpose, a DEM was generated using the version 2.0.1 of Agisoft Metashape

Pro software and the three scenes' panchromatic Pléiades images. The following workflow (Figure 3.4) was used to generate a 1-meter resolution DEM. The first and most important step is to correctly set the model to automatically recognize the Ratio Polynomial Coefficient (RPC) associated with each image. Nonetheless, diffuse clouds and their shadows prevent the fully use of this DEM over the entire study area.

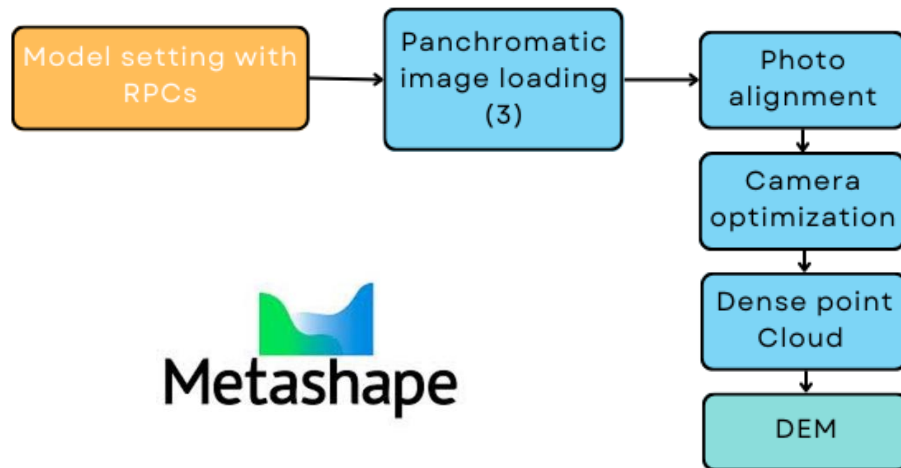


Figure 3.4: Generation of a high-resolution DEM using panchromatic images in Agisoft Metashape software

3.3.2. Image fusion

Pan sharpening is a technique for increasing the spatial resolution of a multiband image by using a high-resolution panchromatic image through data fusion. To achieve this, three original multispectral bands are selected to form a color version, and a hue, saturation, and intensity transformation is applied. The intensity channel is then discarded and replaced with the panchromatic data (ESRI, 2023). The hue and saturation images are then resampled to the spatial resolution of the panchromatic band and transformed back to the red, green, blue color space (Richards, 2022). Moreover, the addition of weighting and enabling the infrared component can enhance the visual quality of the output colors.

The Esri-based pan sharpening algorithm used here is one of several image fusion methods available (Bovey, Gram-Schmidt, IHS, etc.), which uses a weighted average and the additional near-infrared band to create its pan sharpened output bands (ESRI, 2023). The benefit of pan sharpening is to have high-resolution and updated images for synchronization with the field

survey achieved during the image acquisition period. Figure 3.5 shows a capture of the same subset image where (a) is the original ortho-rectified image with 2 m resolution, and (b) is the resulting fusion image with 50 cm resolution. Weights of 0.6, 0.85, 0.75, and 0.3 were adopted for the red, green, blue, and infrared channels, respectively.

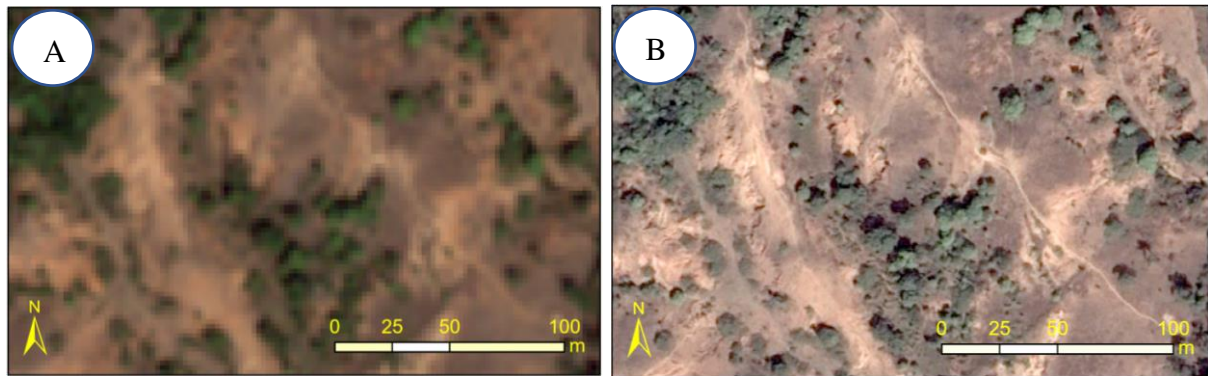


Figure 3.5: Illustration of a subset image before (left) and after (right) pan sharpening

3.3.3. Image registration

Airbus provided an orthorectified version of the multispectral images for which some geometric corrections have already been applied. However, to ensure an accurate delineation of objects reflecting the terrain, all the layers used need to be aligned in the same coordinate system, a process known as image registration (Richards, 2022). Image registration involves using digital image processing techniques to align two or more digital images (Le Moigne et al., 2011). The layers used in this study include a multispectral image, a Digital Terrain model (DTM), and calibration and validation data. All these data have been projected in the same reference system: “WGS 84, UTM Zone 18 N” commonly used for Haiti.

3.4. Field survey

To understand the morphological and distribution characteristics of gullies in the Sainte-Suzanne region of Haiti, a field survey was conducted during the same season as the remote sensing data acquisition. The aim of this field survey was to develop a strong capability for visual interpretation of images in the study area and investigate both hillslope gullies and valley-bottom gullies. Examples of gullies originating on the slopes are provided in Annex B and Annex C, while examples of a valley-bottom gully is shown in Annex A.

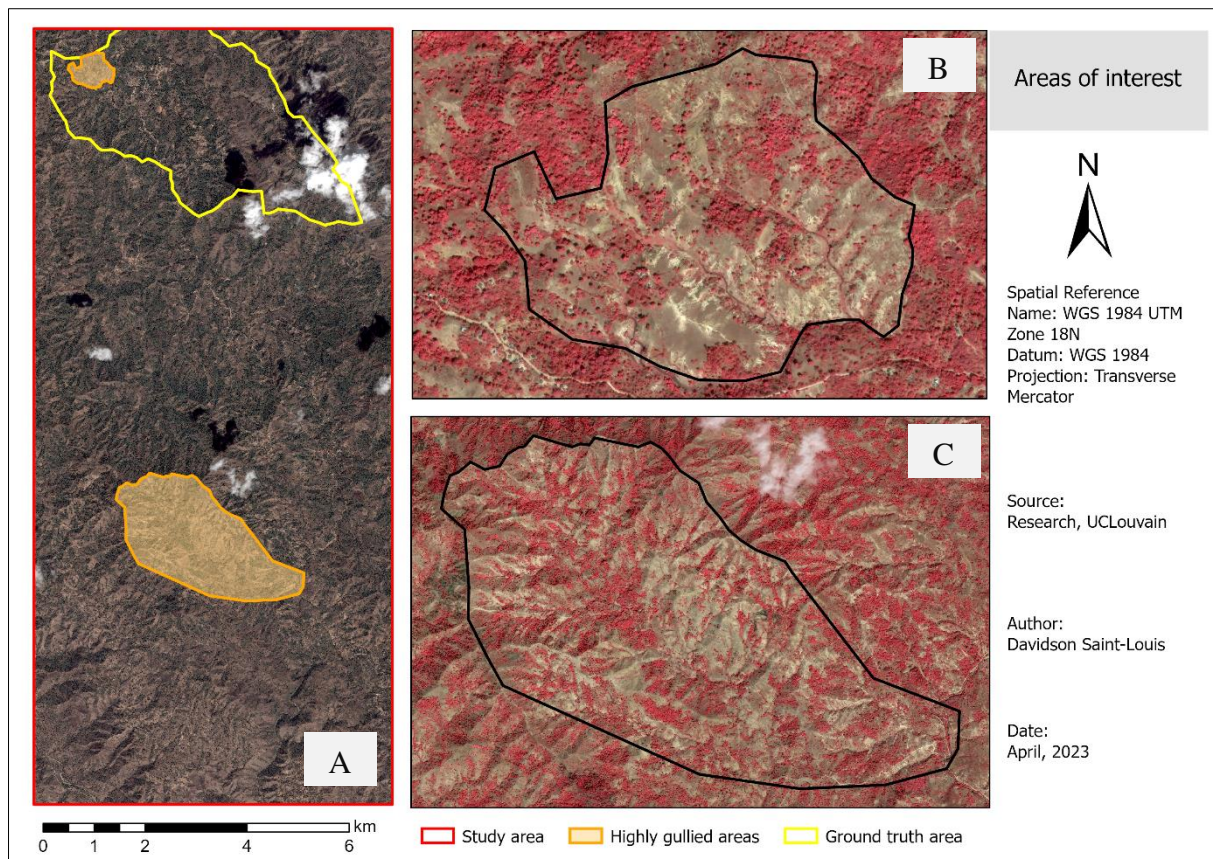


Figure 3.6: Extent of the study area (A), highly gullied area within the ground truth area (B), highly gullied area outside the ground truth area (C)

Initially, the study involved geolocating gullies and gullied areas, measuring channel cross-section and width at the surface, estimating gully depth, and qualitatively assessing the level of erosion for valley-bottom gullies. An electronic survey form was used for data collection, along with metrics tapes and a Garmin GPS with precision up to 1 meter. The slopes are dotted with clusters of ravines, making them almost impossible to be individually georeferenced using a standard GPS. However, the areas affected by this process are often well-defined in space, leading us to use the term "gully-affected area" also named "gullied area" further in this document. The density, width, and depth of these ravines within a cluster serve as markers of the boundary between moderately eroded and highly eroded areas (see photo in Annex D). Only hillslope gullies in areas with high erosion levels have been considered, decreasing uncertainty for calibration data.

Although erosion is present throughout the study area, figure 3.6 highlights two subsets with highly gullied area. One of these highly gullied areas is located within the ground truth area and the other is located outside the ground truth area. They cover an area of 5.72 km².

The training data were digitized, using the orthophoto resulting from the fusion of Pléiades images, with a resolution of 50 cm. The same process was used to validate the non-gullied zones. Therefore, the field data has a much higher certainty than that obtained from aerial images. Given the similarity between some gullied areas and bare soils, only gullied areas with high certainty were selected.

3.5. Image segmentation via eCognition

The approach for gully mapping involves Object-Based Image Analysis on multispectral satellite imagery using eCognition Developer software (version 10.1) from Trimble Geospatial. Several steps were carried out in this research to delineate gully areas. The first step involves a thresholding to discriminate areas with high vegetation cover. Then, an algorithm is used to segment areas with low vegetation cover.

3.5.1. Image segmentation backgrounds

Image segmentation is a crucial step in object-based image processing, as it groups pixels with similar spectral and spatial characteristics into coherent objects (Liu et al., 2017; Mohamadi et al., 2021). This process is necessary for creating new image object levels based on image layer information. ECognition offers 11 segmentation algorithms, including multiresolution segmentation, multi-threshold segmentation, vector, and chessboard segmentation, among others. For this study, multi-resolution segmentation algorithm had been used to delineate gullied areas from the ortho-rectified satellite imagery.

3.5.2. Multiresolution segmentation

Multiresolution Segmentation (MRS) is a region-based approach that follows a bottom-up merging strategy, starting from individual pixels and gradually grouping neighboring pixels with the minimum heterogeneity increment (Liu et al., 2017). The procedure includes a pairwise clustering process to merge smaller objects into larger objects with uniform texture and color, as well as an optimization process defined by a set of parameters, such as scale, color, and

shape. When the spectral and spatial heterogeneity of an object reaches a user-defined threshold, the procedure stops growing (Karami et al., 2015). This algorithm can be executed on an existing image object level or at the pixel level to create new image objects with a specific level of resolution. In general, the pixel level is used for initial segmentation (Trimble, 2023). The MRS algorithm relies on 3 fundamental parameters: scale, shape, and compactness, as shown in figure 3.7.

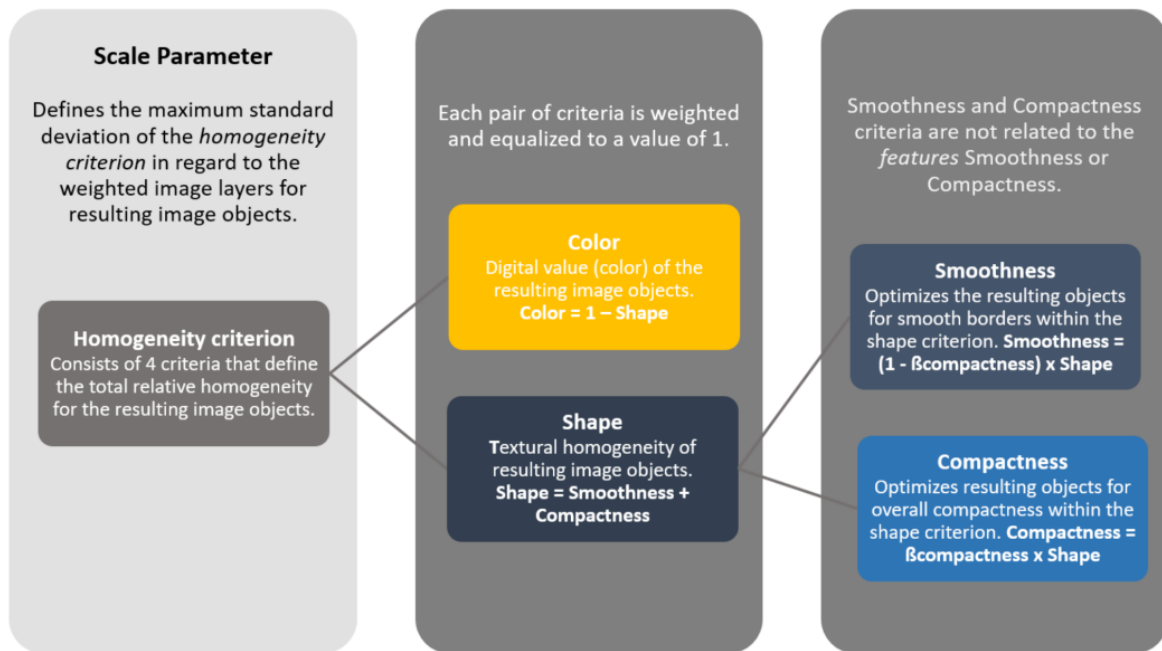


Figure 3.7: Scale parameter and homogeneity criterion (Trimble, 2023) in MRS

The scale parameter determines the maximum allowed heterogeneity for image objects and, by modifying its value, the size of image objects can be changed. The shape field modifies the relationship between shape and color criteria, and decreasing its value defines the percentage to which spectral values contribute to the homogeneity criterion. The compactness criterion optimizes image objects regarding their compactness, and it should be used when different image objects are compact but separated by a weak spectral contrast. Its range is between 0.1 and 0.9 and it is less considered in the segmentation process. The compactness of spatial objects is indeed associated with the concept of image shape. It quantifies the smoothness or regularity of the boundary or shape of a segmented region. Compactness is commonly employed as a criterion or constraint in image segmentation algorithms to facilitate the generation of well-defined and regular segmented regions (Trimble, 2023).

3.6. Metric computation

Beside segmenting images, metric calculation was also conducted. Spectral, textural, and geometric features were calculated for each object. Formulas and description of these features are provided below.

3.6.1. Soil and vegetation indices

3.6.1.1. NDVI

Vegetation indices can be created using composite band arithmetic operations. The most widely encountered uses the ratio of the difference and sum of reflected infrared and visible red reflectance (Richards, 2022). It is generally referred to as the Normalized Difference Vegetation Index (NDVI). It is often used to measure the amount and density of vegetation in a given area. NDVI values range from -1 to 1, where positive values indicate the presence of dense vegetation, while negative values indicate the presence of non-vegetated surfaces such as water or bare soil. It is determined by equation 3-1. This index will be used during image segmentation to define a threshold between areas with high vegetation and areas with low vegetation cover.

$$NDVI = \frac{NIR_{reflectance} - Red_{reflectance}}{NIR_{reflectance} + Red_{reflectance}} \quad [3-1]$$

3.6.1.2. NDSI

Normalized Difference Soil Index (NDSI) is a remote sensing index that is used to identify bare soil areas in satellite imagery. It is calculated as presented in equation 3-2:

$$NDSI = \frac{Red_{reflectance} - Blue_{reflectance}}{Red_{reflectance} + Blue_{reflectance}} \quad [3-2]$$

NDSI values range from -1 to 1, with higher values indicating the presence of bare soil and lower values indicating the presence of vegetation or other features (Trimble, 2023).

3.6.1.3. SAVI

Soil Adjusted Vegetation Index (SAVI) is a vegetation index that considers the soil background reflectance to improve the accuracy of vegetation monitoring in areas with high soil brightness

(Trimble, 2023). It is like the NDVI but has an additional factor L (standing for Landsat), as shown in equation 3-3.

$$SAVI = \frac{NIR_{reflectance} - Red_{reflectance}}{(NIR_{reflectance} + Red_{reflectance} + L)} * (1 + L) \quad [3-3]$$

L is the soil adjustment factor in a range from [0,1]. Its value varies with vegetation density: **L = 0** – dense vegetation. For L=0, SAVI = NDVI. A commonly used value for L is 0.5 (Laliberte et al., 2007; Trimble, 2023).

3.6.2. Slope derivative

The Zevenbergen-Thorne method is a widely used algorithm for calculating slope from elevation data. In eCognition, slope algorithm relies on this method. It calculates the slope by fitting a plane to the neighboring pixels around each point and determining the slope of that plane. The resulting slope values can be expressed as a percentage, as is the case in this study. This metric was used exclusively in classification task.

3.6.3. Textural indices

Texture is an important descriptor of an image which uses the spatial arrangement of gray values for image analysis (Ramola et al., 2020). The Gray Level Co-occurrence matrix (GLCM), first proposed by Haralick (1979), is a commonly used methodology for texture analysis. The GLCM is a tabulation of how often different combinations of pixel gray levels occur in a scene. A different co-occurrence matrix exists for each spatial relationship. When calculating the GLCM from an input image, two factors are considered most important, that is, the distance ranging from 1 to 4 and the orientation angle, according to Armi and Fekri-Ershad (2019). To ensure directional invariance, the sum of all four directions (0°, 45°, 90°, 135°) is calculated before texture calculation. An angle of 0° represents the vertical direction, while an angle of 90° represents the horizontal direction (Trimble, 2023).

Among these indices, homogeneity, contrast, and entropy are the most used in remote sensing for discriminating areas affected by gully erosion (Mohamadi et al., 2021; Shruthi et al., 2015) as example. The window size, which ranges from 3x3 to 15x15, plays an important role in the calculation of these indices. In the case of this study, the basic window size of 3x3 was used to

capture the texture at an appropriate scale. The calculation of these indices was performed using Orfeo ToolBox, an open-source tool (Annex J). The textures are calculated in channel 1, which corresponds to the red band based on the flow direction raster.

3.6.3.1. *Homogeneity*

Homogeneity is a texture feature that measures the similarity of gray-level values in an image region. It is calculated based on the GLCM and is defined as the sum of the products of the GLCM elements divided by the square of the distance from the GLCM diagonal (equation 3-4). Homogeneity is high when the values of pixels in the image region are similar, resulting in a concentration of high values along the diagonal of the GLCM (Trimble, 2023).

$$Homogeneity = \sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2} \quad [3-4]$$

The denominator acts as a weighting factor, decreasing exponentially with increasing distance from the diagonal of the GLCM, giving more weight to values that are closer to the diagonal.

3.6.3.2. *Contrast*

Texture contrast is a measure of the difference in gray-level values between a pixel and its neighbors in the GLCM (equation 3-5). It provides information on the variation in texture across the image. The contrast is calculated by summing the product of the squared differences between the gray-level values and their means in the GLCM. A higher contrast value indicates a greater variation in texture across the image (ibid.).

$$Contrast = \sum_{i,j=0}^{N-1} P_{i,j} \times (i - j)^2 \quad [3-5]$$

3.6.3.3. *Entropy*

Texture entropy provides information about the texture complexity, randomness, and heterogeneity of different regions within an image. It can be used in various tasks such as image segmentation, classification. The entropy value is high if the elements of GLCM are distributed equally, indicating a high degree of randomness or complexity in the texture (equation 3-6). Conversely, the entropy value is low if the elements are close to either 0 or 1, indicating a more predictable or uniform texture. Mathematically, entropy is calculated as:

$$Entropy = \sum_{i,j=0}^{N-1} P_{i,j} \times (-\ln P_{i,j}) \quad [3-6]$$

With

- i: the row number,
- J: the column number,
- $P_{i,j}$ is the normalized value in the cell i, j
- N is the number of rows and columns.

Instead of using GLCM, another method for texture measurement is to employ a Gray-Level Difference Vector (GLDV), obtained by summing the diagonal elements of the GLCM. It represents the occurrences of absolute differences between neighboring pixels (Trimble, 2023). This feature has been experimented in this study to enhance gully delineation.

3.7. Object-based classification of the image

Following the segmentation of the images, polygonal objects were extracted from eCognition for classification. A binary classification will determine the membership of each polygon to the gully class. To accomplish this, two machine learning algorithms have been applied: Decision Trees and Random Forest.

3.7.1. Random Forest and Decision Trees classifiers

3.7.1.1. Decision Trees classifier

Decision Trees (DT) are a popular machine learning algorithm used for classification and regression tasks (like Random Forests). The main difference between them is in how they construct the model. Decision Trees recursively split the data based on the feature that best separates the data into different classes or groups. At each node of the tree, the algorithm selects the feature that provides the best information gain and splits the data based on the values of that feature. This process continues until all the data are classified into their respective groups (Rokach and Maimon, 2005). Authors such as Laliberte et al. (2007) have reported that Decision Trees often outperform other classifiers such as maximum likelihood and linear discriminant function classifiers. One of the main advantages of Decision Trees is that they are computa-

tionally fast and make no statistical assumptions regarding the distribution of data (Otukey and Blaschke, 2010). This makes them a useful tool in cases where the data is complex or non-linear and traditional statistical methods may not be effective.

3.7.1.2. What is Random Forest?

Random Forest (RF) is a machine learning algorithm that is part of the ensemble learning family. It is composed of a collection of trees, or a "forest", that are constructed in a random manner (Richards, 2022). This is achieved by taking a random sample of the data and creating an ongoing series of decision trees on the subsets. It is a supervised learning algorithm that can be used for both classification and regression tasks (Gall et al., 2012; Genuer et al., 2010). According to Breiman (2001), random forests are a procedure whereby trees vote for the most popular class after many trees are generated. In Object-Based Image Analysis, the actual label assigned to an unknown object is determined by the most favored label among the trees, called modal logic by Richards (2022). The fundamental concept of the algorithm is to create multiple decision trees (Figure 3.8) and combine their results to make a final prediction. Each tree consists of split nodes and leaves. The split nodes assess each arriving image patch and pass it on to the left or right child based on its appearance. Each leaf stores the statistics of the image patches that arrived during the training process (Gall et al., 2012).

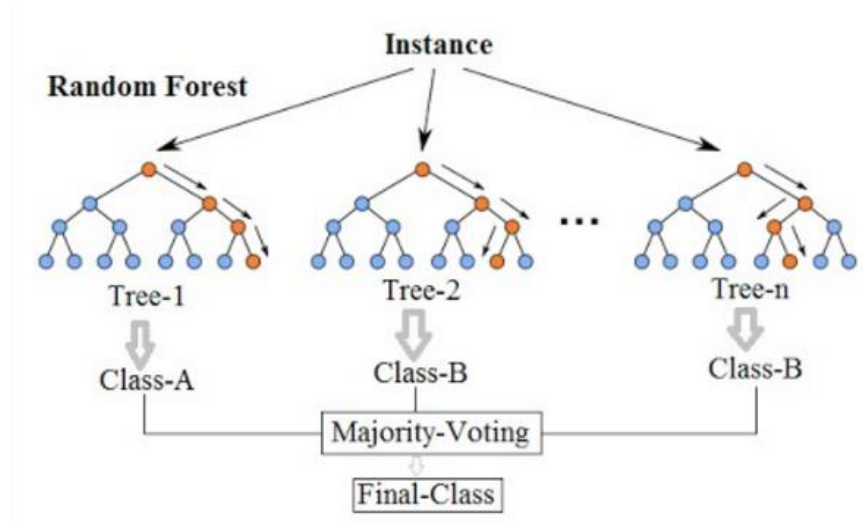


Figure 3.8: Overview of a simplified Random Forest (Venkata, 2023)

3.7.2. Training and validation data

3.7.2.1. Dataset composition

Six object classes were defined to represent different land cover types: forest, roads, bare soil, low vegetation, built-up areas, and eroded areas. The allocation of data points for each class was based on a visual estimation of their surface frequency in the study area, aiming to prevent model overlearning. The visual estimation was supplemented by thresholding the NDVI (section 3.5), revealing that areas with NDVI values exceeding 0.40 accounted for 48% of the study area. Table 3.2 provides the estimated surface percentage for each land cover class, with the number of data points for the “Eroded area” class serving as a reference to determine the data distribution for the other classes.

Table 3.2: Origin of data samples (point shape) and their distribution by class, with a preliminary estimation of the area of each class

Class	Area (%)	Number of training and validation points		
		All	Ground truth	Image
Eroded area	10%	162	48	114
Roads	3%	41	0	41
Builtup	3%	41	0	41
Bare soil	10%	154	0	154
Low vegetation	26%	413	0	413
Forest	48%	760	0	760
Total	100%	1570	48	1522

A field visit was conducted to establish a ground truth area, as illustrated in Figure 3.6. Within this area, 48 “Eroded area” (gullied areas) samples (points) were georeferenced on the ground. The complementary 114 gullied area samples, along with all the samples for other classes, were derived from visual interpretation of the available image for the study area. Image-derived sample points were systematically distributed across the study area, with a higher density in highly gullied areas. Image areas affected by clouds and shadows were not sampled.

3.7.2.2. Calibration and validation data split

To assess the performance of the Random Forest and Decision Trees models, the data set was divided into calibration and validation sets (Table 3.3). Specifically, for the "Eroded area" class, the data set was split as follows:

- ✓ 80% for calibration (130 gully points)
- ✓ 20% for validation (32 gully points)

Table 3.3: Data distribution between calibration and validation samples (point shape)

Class	All	Calibration	Validation
Eroded area	162	130	32
Roads	41	35	6
Builtup	41	35	6
Bare soil	154	148	6
Low vegetation	413	406	7
Forest	760	753	7
Total	1570	1506	64

For the "Eroded area" class, 32 validation points were randomly chosen from the 48 ground truth points. The remaining 16 points, along with the 114 points obtained from image interpretation, were allocated for calibration (130 samples).

For the five other classes, there were no specific constraints regarding location or ratio between validation and calibration. However, since the final goal is a binary classification between "gullied areas" and "non-gullied areas," it was important to ensure an equal distribution of data points for each of these two super-classes. This approach enables an independent assessment of accuracy between the assigned class after training and the ground truth. Therefore, 50% of the samples were assigned to the "Gullied area" class, while the remaining 50% were assigned to the "Non gullied area" class, resulting in a total of 64 samples allocated for accuracy assessment.

The 32 points for the "Non gullied area" superclass were also randomly selected (Annex G), while considering the constraint on the number of data points for each class (Table 3.3). The sampling design for both calibration and validation data can be observed in Annex F.

3.7.2.3. Point samples to object samples

The calibration dataset (points) was imported into eCognition. The "Assign class by thematic layer" and "supervised image object to sample" algorithms were then utilized to automatically assign classes and define the surrounding objects as training samples. The names of these algorithms vary depending on the version of eCognition, but their functionality remains the same. Both the Random Forest and Decision Trees classifiers were trained and executed within the eCognition environment.

Following the training and execution of the classifiers, the classification results were exported as shapefiles to preserve the georeferencing of the objects. By leveraging spatial topology, validation polygons are extracted from the dataset using ArcGIS Pro software. Finally, an accuracy assessment was conducted between the model predictions and the ground truth data using confusion matrices. This step was completed in Python, using the Google Colab API (Automatic Programming Interface).

3.7.3. Model parametrization

The RF model was trained using data from test polygons comprising 25 features described in the next section. The RF model is controlled by two main parameters: (a) the number of trees in the forest (nTree), (b) the number of input variables (predictors) randomly chosen at each split (mtry), according to Genuer et al. (2010). Most studies have set nTree to 500 and mTry to the square root of the number of input variables (Liu et al., 2017). Due to the large size of the study area and the resolution of the image, it took a long time for the model to converge when using 500 trees. As a result, a reduced number of trees was used instead. This decision was made to optimize computational resources and improve the efficiency of the modeling process. Thus, the RF model builds an ensemble of 100 decision trees using a random selection of 2 predictor variables (features) at each split (tree). This technique of building multiple decision trees with random feature subsets and aggregating their predictions helps to reduce overfitting and improve the generalization performance of the model (Guyon and Elisseeff, 2003).

For Decision Trees, when performing cross-validation, the dataset is divided into k equally sized folds. A fold refers to a subset or partition of the dataset created during the cross-validation process. The model is then trained on $k-1$ folds and tested on the remaining fold. This process is repeated k times, with each of the k folds used exactly once as the validation data. The results of the k iterations are averaged to produce a final performance metric for the model (Laliberte et al., 2007). Three cross-validation folds have been used, meaning that the dataset was divided into 3 equally sized folds, and the model was trained and tested on each of these folds in turn, with the results averaged at the end.

3.7.4. Prediction variable or features

On eCognition, samples can be in the form of points, lines, or polygons. Given the high precision of the segmentation that follows the shape of objects, point sampling was chosen. Initially, 25 features including spectral, textural, geometric, and thematic were tested in the classification process as suggested in Table 3.4. Thematic layers include slope and altitude, derived from the DEM. Textures are calculated from the flow direction, also derived from the DEM. Gini index or Gini impurity was determined to figure out the involvement of each of those features in the classification process.

Feature number refers to an alphabetical ranking associated with each feature from eCognition, and it is used as such for the sake of consistency in the Python environment. It subsequently allows linking the importance of each feature to their corresponding names.

Table 3.4: Overview of the 25 features used in gully mapping including the assigned number, the mathematical expression and meaning (Trimble, 2023)

Feature type	Title and feature number	Mathematical expression and meaning
Spectral	Mean: Red (18), Green (13), Blue (11)	Features in this group refer to the mean layer intensity value of an image object. $\bar{c}(v) = \frac{1}{w^B} \sum_{k=1}^K w_k^B \bar{c}_k(v)$
	Mean NIR (17)	
	Mean NDVI (16)	
	Mean NDSI (15)	
	Mean SAVI (14)	

Feature type	Title and feature number	Mathematical expression and meaning
	Mean brightness (2)	w_k^B (Brightness weight), K (number of image layers), w^B (sum of brightness weights), $\bar{c}_k(v)$ (mean intensity of image layer) of object v .
	Std Green (24)	The standard deviation is calculated from the image layer intensity values of all pixels forming an image object. $\sigma_k(v) = \sqrt{\frac{1}{\#P_v} \left(\sum_{(x,y,t) \in P_v} c_k^2(x,y,t) - \frac{1}{\#P_v} \left(\sum_{(x,y,t) \in P_v} c_k(x,y,t) \right)^2 \right)}$ P_v is the set of pixels of an image object v $\#P_v$ is the total number of pixels contained in P_v $C_k(x, y, t)$ is the image layer intensity value at pixel coordinates (x, y, t)
	Std NIR (22)	
	Std NDVI (23)	
	Max difference index (10)	$\frac{\max_{i,j \in K_B} \bar{c}_i(v) - \bar{c}_j(v) }{\bar{c}(v)}$ $\bar{c}_i(v)$ is the mean intensity of image layer of i image object v and $\bar{c}_j(v)$ is the mean intensity of image layer j of image object v.
Geometric	Area (polygon): (0)	This feature calculates the area of a polygon. The feature value does not include the areas of any existing inner polygons. $\frac{1}{2} \sum_{i=0}^{n-1} a_i$ $(x_i, y_i), i = 0, \dots, n$, with $x_0 = x_n$ and $y_0 = y_n$ as the given points, $a_i = x_i y_{i+1} - x_{i+1} y_i$
	Length/width (9)	The ratio of length to width can also be approximated using the bounding box. $\gamma_v^{BB} = \frac{(k_v^{BB'})^2}{\#P_v}$ γ_v^{BB} is the ratio length of v the bounding box $k_v^{BB'}$ is the width of the bounding box of the image object.
	Rectangular fit (20)	The Rectangular fit feature describes how well an image object fits into a rectangle of similar 0 size and proportions. While 0 indicates no fit, 1 indicates for a complete fitting image object. $\frac{\#\{(x, y) \in P_v : \rho_v(x, y) \leq 1\}}{\#P_v}$ $\rho_v(x, y)$ is the elliptic distance at a pixel (x, y).

Feature type	Title and feature number	Mathematical expression and meaning
	Density (4)	$\frac{\sqrt{\#P_v}}{1 + \sqrt{\text{Var}X + \text{Var}Y}}$ $\sqrt{\text{Var}X + \text{Var}Y}$: is the diameter of the ellipse. $\sqrt{\#P_v}$ is the diameter of a square object.
	Compactness (3)	$\frac{l_v w_v}{\#P_v}$ l_v is the length of an image object v . w_v is the width of an image object v .
	Asymmetry (1)	The Asymmetry feature compares an image object with an approximated ellipse around the given image object. The calculation is based on the variance in x-direction and y-direction, which results in a feature value that increases with an increasing image object asymmetry. $\frac{2\sqrt{\frac{1}{4}(\text{Var}X + \text{Var}Y)^2 + (\text{Var}XY)^2} - \text{Var}X \cdot \text{Var}Y}{\text{Var}X + \text{Var}Y}$ $\text{Var}X, \text{Var}Y$ are respective X and Y variance.
	Shape index (21)	The Shape index is a measure of overall shape complexity. The feature value is 1 for compact objects and increases without limit for more irregular shapes. It is calculated from the border length feature of the image object divided by four times the square root of its area. $\frac{b_v}{4\sqrt{\#P_v}}$ b_v is the image object border length.
GLCM Textural (From flow direction)	Contrast (5)	Described in section 3.6.3
	Entropy: GLDV (8), GLCM (6)	
	Homogeneity (7)	
Thematic (from the DEM)	Slope (19)	Described in section 3.6.2
	Elevation (12)	Elevation is derived from the DEM

3.7.5. *Features reduction*

Random Forest is a powerful classification algorithm, but it can be memory-intensive and take longer to execute compared to Decision Trees. To overcome these issues, it is a common practice to reduce the dimensionality of the data by selecting only the most significant features for classification. The objective of feature selection is to improve the prediction performance of the model, provide faster and more cost-effective predictions, and gain a better understanding of the underlying data-generating process (Guyon and Elisseeff, 2003). Feature selection can be performed using various methods such as the Gini index or Principal Component Analysis (Richards, 2022). The subset of selected features can be reused to improve classification accuracy and reduce computation time. It is essential to note that feature selection should only be performed on the training data to avoid overfitting and ensure the generalization ability of the model.

The most used impurity measure in Classification and Regression Trees (CART) is Gini Impurity which measures the divergences between the probability distributions of the target attribute's values (Rokach and Maimon, 2005). The Gini index ranges from 0 to 1; it is equal to 0 if all observations in a node belong to the same class, and it is 1 when different class sizes at the node are equal (Laliberte et al., 2007).

According to Richards (2022), Gini Index is defined at the Nth node as:

$$i(N) = \sum_j P_{\omega j} (1 - P_{\omega j}) \quad [3-7]$$

in which $P_{\omega j}$ is the fraction of the training pixels at node N that are in class ωj ; $1 - P_{\omega j}$ is the proportion not in class ωj .

3.8. Accuracy assessment

It is crucial to evaluate the accuracy of the results obtained at the end of a classification task to ensure their reliability and determine whether the objectives of the analysis have been achieved (Richards, 2022). There are several tools available to assess the accuracy of a thematic map, and various measures can be used to express this accuracy (Shruthi et al., 2015). In this study, we used the confusion matrix and F-Score measurement to evaluate the accuracy of the results.

From the error matrix, User's accuracy (UA) and Producer's Accuracy (PA) are calculated to obtain the combined F-Score measure (equation 3.8). PA is the fraction of correctly classified objects with respect to all objects of a ground truth class, while UA is the fraction of correctly classified objects (or pixels) with respect to all objects classified as a particular class in the classified image (Richards, 2022). Accuracy calculates the ratio of correct predicted classes to the total number of samples evaluated (Alzubaidi et al., 2021). The accuracy assessment of the gully mapping was first calculated for the number of detected objects. After, results have been translated into surface, to get the extent of gullied area.

$$F - score = 2 \times \frac{Precision * Recall}{Precision + Recall} \quad [3-8]$$

For a given class, the user's and producer's accuracy are:

$$PA_i = Recall = \sum_{j=1}^r \frac{n_{ii}}{n_{ji}} = \frac{TP}{TP+FP} \quad [3-9]$$

$$UA_i = Precision = \sum_{j=1}^r \frac{n_{ii}}{n_{ij}} = \frac{TP}{TP+FN} \quad [3-10]$$

With “ r ” the number of classes, and i, j , the respective line and column of class “ i ” of the error matrix.

$$OA = Overall Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad [3-11]$$

TN and TP are defined as the number of negative and positive instances respectively, which are successfully classified. In contrast, FN or omission error and FP or commission error are defined as the number of misclassified positive and negative instances respectively.

4. RESULTS

In this chapter, we present the results obtained from the methodology adopted in **Chapter 3**. The first part describes the process of image segmentation. The second part analyzes the results of the image classification, including the performance of detection using two distinct methods: Decision Trees and Random Forest. Next, some statistics regarding the created objects are provided. Finally, an analysis of the generated DEM using Pléiades imagery and a summary regarding valley-bottom gullies are provided.

4.1. Image segmentation

The multi-resolution segmentation algorithm was used to partition the image into distinct objects. Prior to this, a thresholding operation had been carried out to estimate the importance of each class of objects in the landscape. For instance, a NDVI threshold of 0.4 was applied to calculate the extent of dense vegetation where erosion expectation is lesser. Consequently, areas with high NDVI values, indicating dense vegetation, comprise 52% of the study area, while the rest of the surface is apportioned among various landscape elements. Gullied areas were initially projected to occupy 20% of the space for elements with NDVI values less than 0.4, which corresponds to 10% of the total study area (first estimation). The MRS algorithm generated 386,073 segments or objects.

After a lengthy calibration process, the combination of different layers and the weights assigned to them allows for the creation of objects that follow the patterns observed in the field. We used the multiresolution segmentation method in eCognition 10.1, based on 11 parameters. Scale, shape, and compactness are mandatory in eCognition. The available Red, Blue, Green, and NIR channels of the pan sharpened Pléiades image were used, along with some vegetation indices and the elevation layer (CNIGS DEM).

The process of finding the optimal value for the scale parameter requires manual calibration. In our study, we prioritized over-segmentation to minimize the possibility of having objects that belong to different classes. After testing different values from the default, scale value ranges from 70 to 100 can be used for gully delineation. But a scale value of 100 was determined to be the most suitable for the ground pattern. Since gullies reflectance can be variable, the shape parameter was given a higher weight than color, with a value of 0.7. This implies that color was

implicitly assigned a value of 0.3. The compactness parameter was set at 0.5, meaning that smoothness was given equal weight. Additionally, several layers were used to better delineate gullied areas, as outlined in table 4.1. Weights of two were assigned to NIR and red reflectance, and to the NDVI index due to their sensitivity to water and vegetation cover, as reported by many studies, for example Shahabi et al. (2019).

Table 4.1: Optimal segmentation parameters after four iterations

Scale	Shape	Compactness	Layer weights							
			Red	Green	Blue	NIR	NDVI	NDSI	SAVI	DEM
100	0.7	0.5	2	1	1	2	2	1	1	1

Figure 4.1 provides an overview of a subset (a portion) of the image in the study area and its corresponding segmentation result, which includes the objects identified through the application of optimal segmentation parameters.

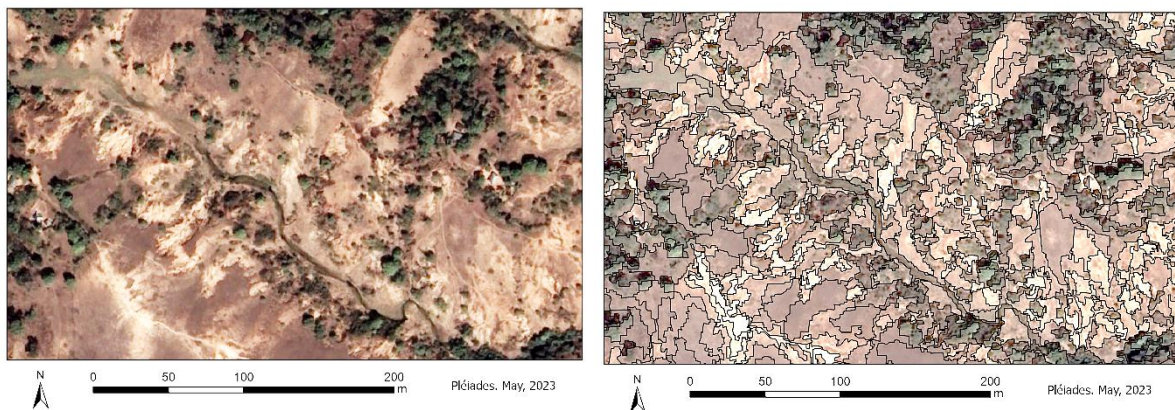


Figure 4.1: An image subset from the study area (A) and its segmented equivalent

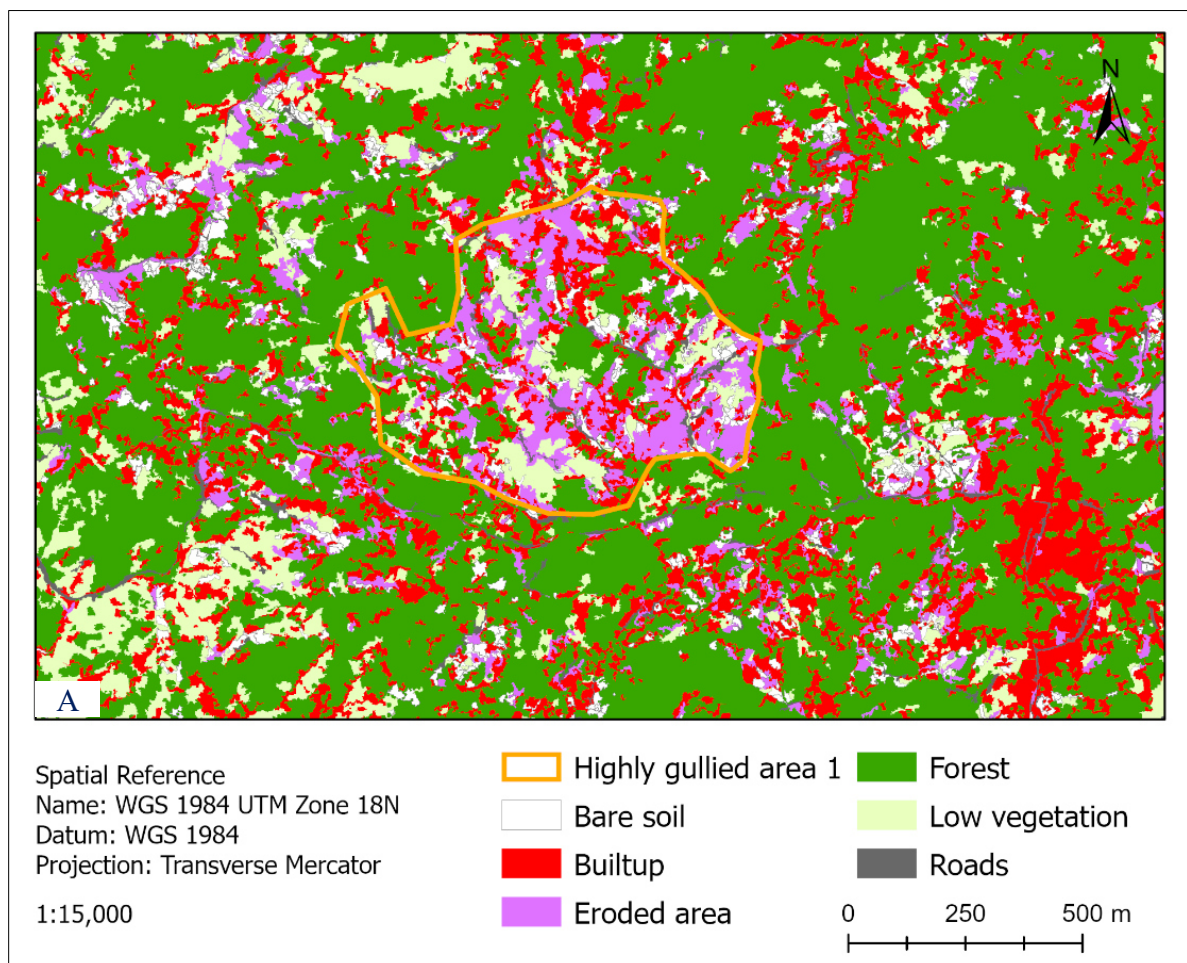
4.2. Classification

The classification was performed after segmentation on eCognition for both Decision Trees and Random Forest. After training and executing the models, objects were exported in shapefile format. The features used as prediction variables for classification, as well as the class of objects, were selected as attributes of these objects. Next, the results of the image classification were compared with ground truth data by crossing the spatial topology of validation points and

predicted object classes. The two confusion matrices, as well as the calculation of metrics using the scikit-learn Python library, allowed for the evaluation and comparison of the performance of these two models. Lastly, Gini impurity was computed to figure out the importance of each feature used in the classification.

4.2.1. Multi-label classification

Firstly, a general classification like a land-cover map was performed, including six classes: forest, low vegetation, eroded area, built-up area, roads, and bare soil, as shown in figure 4.3. Metrics such as recall, precision, and F1-score were determined for the “eroded area” class, and the overall accuracy was computed. Since the segmentation process accurately delineated gullied areas in the field, it was convenient to use the formed segments for statistics. Thus, the results obtained at this level are based on the number of objects detected in each class, but do not mention yet the extent of the eroded areas.



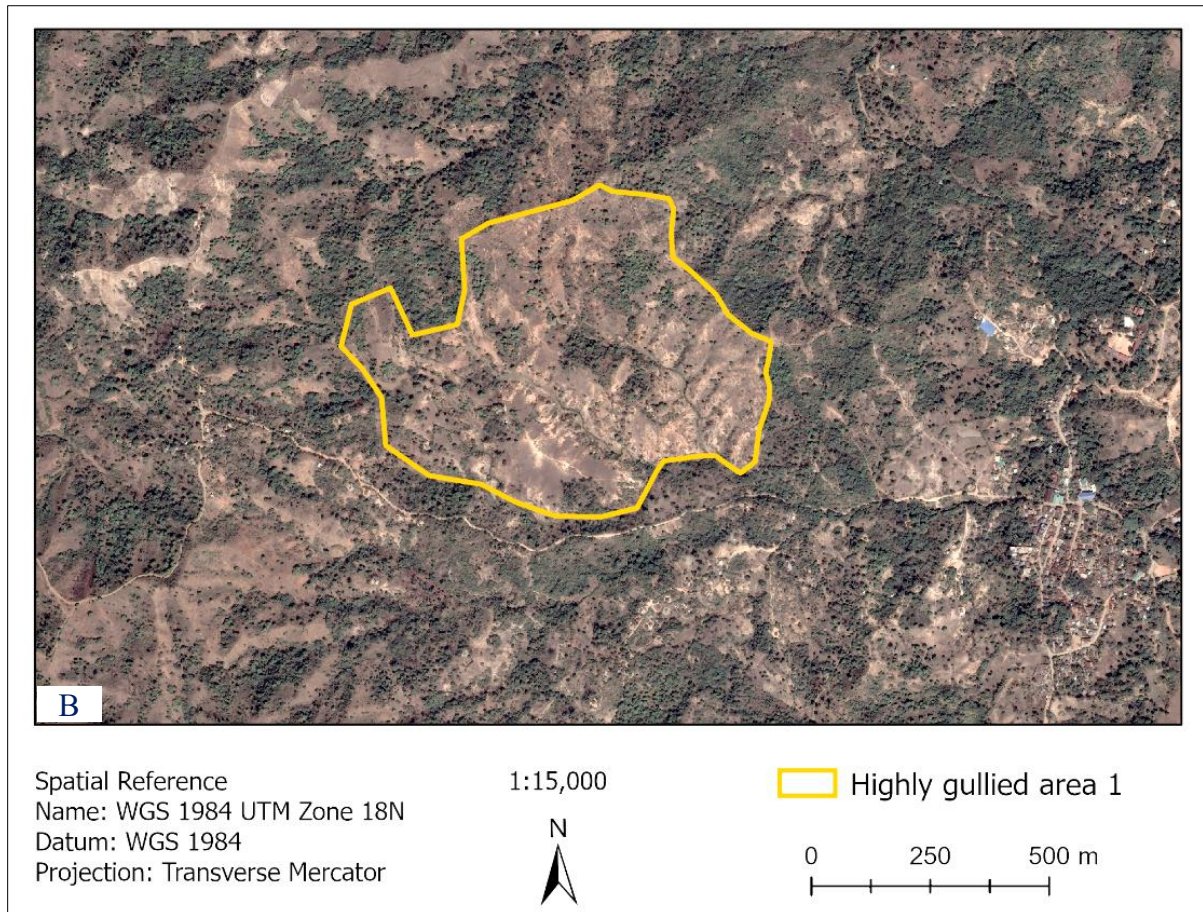


Figure 4.2: Random Forest classification on a subset of the image (A) and the equivalent original image (B)

Figure 4.2 shows the result of the RF classification with a focus on a highly gullied area. Although results will ultimately be a binary classification between non-eroded and eroded areas, the multi-label classification allows testing the model's robustness in predicting other landscape elements. Furthermore, given the strong similarity in reflectance between eroded areas and bare soil, mapping these elements allows for a better assessment of the extent of gully erosion.

Following the thresholding applied to dense vegetation areas, classification of the image was performed. All six classes can be observed in this part of the study area in figure 4.2 A. However, based on our knowledge of the terrain and the high resolution of the image, there is an over-representation of the built-up class.

A more in-depth performance evaluation allowed for further analysis of the results obtained from this first classification. Nevertheless, it has been demonstrated that it is possible to extend

these models to larger areas. Figure 4.3 allows visualization of the classification results for the entire extent of the study area using the two methods mentioned above.

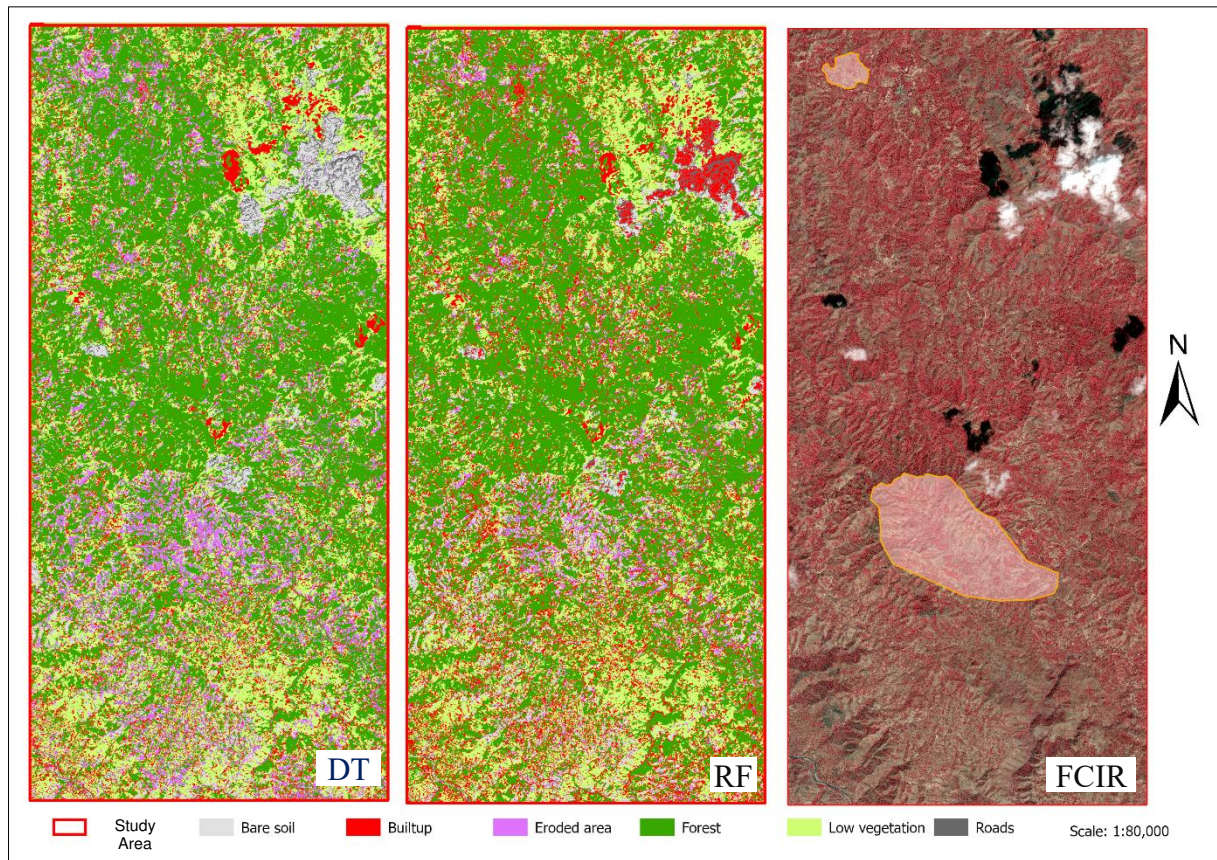


Figure 4.3: False color infrared (FCIR) with the two highly eroded areas, and multi-label classification using Decision Trees (DT) and Random Forest (RF) classifiers.

Visually, the results obtained with both models appear quite similar for the vegetation zones (low vegetation and forest). However, the difference is more noticeable for the eroded areas, especially for the southern part of the study area where there is an over representation with Decision Trees. This statement is based on the visual interpretation of this part of the image, which shows an agricultural plateau, with a gentle slope but bare during the dry season. Random Forest and Random Trees classify clouds differently, but this has little importance for the binary classification performed later. It is also observed that the two areas of high erosion density delimited on the false-color infrared image correspond well to the detection of both models.

4.2.2. Accuracy assessment

To complete the accuracy assessment, object shapes including assigned classes were exported and processed on ArcGIS Pro. Prediction and validation dataset were stored in a CSV format and imported into the Python environment and processed using Google Colab API (Annex H). The results obtained show better performance in terms of Producer Accuracy (Recall) for Decision Trees, which is 100% (Figure 4.4) for “Eroded area” class. This result means that all objects on the map corresponding to “Eroded area” object on the ground are correctly classified. To better appreciate the reliability of this result, it is important to analyze it in terms of precision. Indeed, the Precision is 80%, which means that 20% of objects on the map assigned to the "eroded area" class belong to other classes, mainly the "bare soil" class. These are therefore false positives or commission error. These results suggest an overestimation of gully erosion with this classifier.

On the other hand, Random Forest displays better results for all the other metrics. It is better in Overall Accuracy (0.86), precision (0.94), and F-score (0.92), while still maintaining a good result for Recall (0.91). Therefore, the Random Forest model appears more suitable for gully detection in Haiti, particularly at the watershed of the Grande Rivière du Nord.

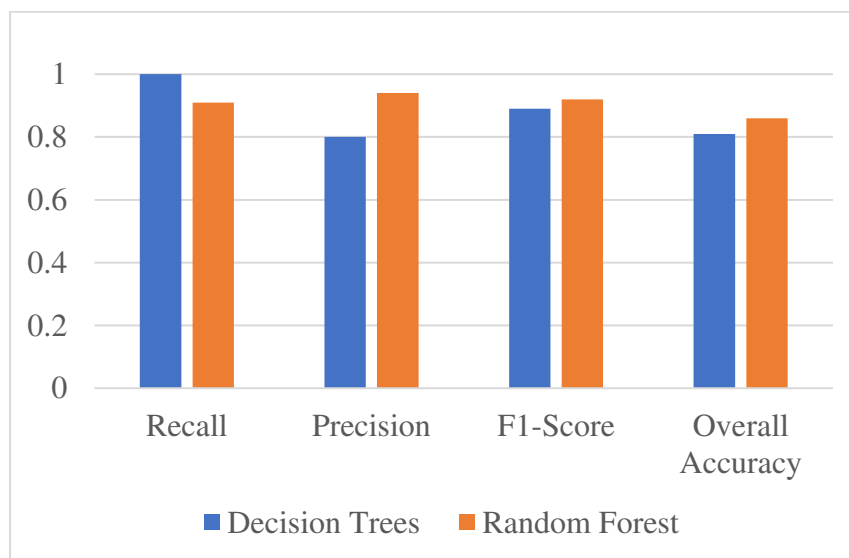


Figure 4.4: Comparison of results for Decision Trees and Random Forest. Recall, precision, and F1-score are calculated for “Eroded area” class. This performance assessment is based on field observations of gullied areas.

The results used for the accuracy assessment are derived from the two confusion matrices obtained with classification using Decision Trees (Table 4.2) and Random Forest (Table 4.3). Metrics are calculated for all the six classes with an emphasis on the “Eroded area” class which has priority in this study.

Table 4.2: Confusion matrix resulting from classification with Decision Trees

		Ground truth data						TP + FP
		Bare soil	Builtup	Eroded area	Forest	Low vegetation	Roads	SUM
Prediction [Map]	Bare soil	2	1	0	0	2	0	5
	Builtup	0	2	0	0	0	0	2
	Eroded area	3	3	32	0	0	2	40
	Forest	0	0	0	7	0	0	7
	Low vegetation	1	0	0	0	5	0	6
	Roads	0	0	0	0	0	4	4
TP + FN	SUM	6	6	32	7	7	6	64
	OA	0.81						
	PA	0.33	0.33	1.00	1.00	0.71	0.67	
	UA	0.40	1.00	0.80	1.00	0.83	1.00	
	F-Score	0.36	0.50	0.89	1.00	0.77	0.80	

Table 4.3: Confusion matrix resulting from classification with Random Forest

		Ground truth data						TP + FP
		Bare soil	Builtup	Eroded area	Forest	Low vegetation	Roads	SUM
Prediction [Map]	Bare soil	5	0	1	0	2	0	8
	Builtup	0	6	2	0	0	1	9
	Eroded area	0	0	29	0	0	2	31
	Forest	0	0	0	7	0	0	7
	Low vegetation	1	0	0	0	5	0	6
	Roads	0	0	0	0	0	3	3
TP + FN	SUM	6	6	32	7	7	6	64
	OA	0.86						
	PA	0.83	1.00	0.91	1.00	0.71	0.50	
	UA	0.63	0.67	0.94	1.00	0.83	1.00	
	F-Score	0.71	0.80	0.92	1.00	0.77	0.67	

4.2.3. Feature importance

During the training process, 25 features were used. Figure 4.5 highlights the importance of prediction features in the classification.

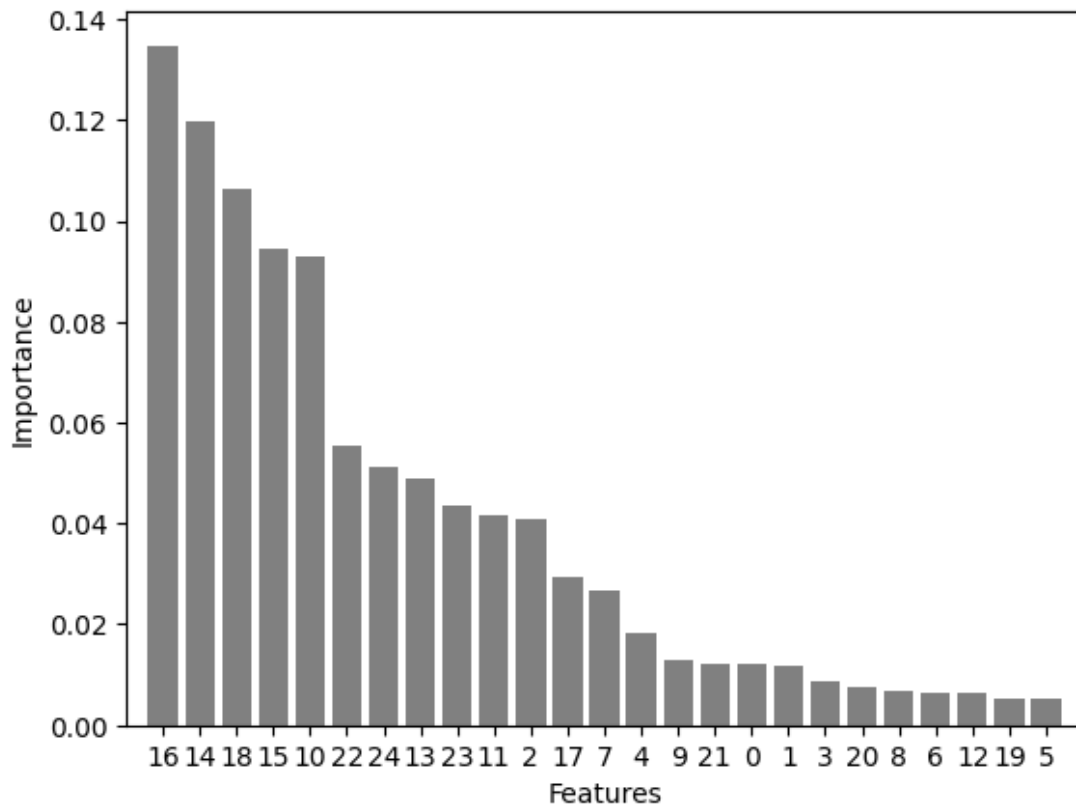


Figure 4.5: Importance (Gini index) of the 25 features in the overall classification. The features corresponding to the numbers on the x-axis are provided in Table 4.4

When training the classifier, the Gini index is calculated for each input feature (code in Annex I). The results indicate that spectral indices are more crucial than other features. Specifically, the NDVI comes on top with a score of 0.13, followed respectively by the SAVI, which is close to the NDVI, the mean red reflectance, the NDSI and the maximum difference. These five are the most important features and they show a large gap with the closest following set. The latter include standard deviation of NDVI, Green, NIR reflectance, the brightness and the GLCM textural homogeneity. The shape indices and thematic layers related to elevation data display the lowest scores ranging from 0.0052 to 0.0182. Table 4.4 provides the name, rank, domain, and Gini value of each feature used in the classification (RF). The column “Feature #” links Table 4.4 to Figure 4.5.

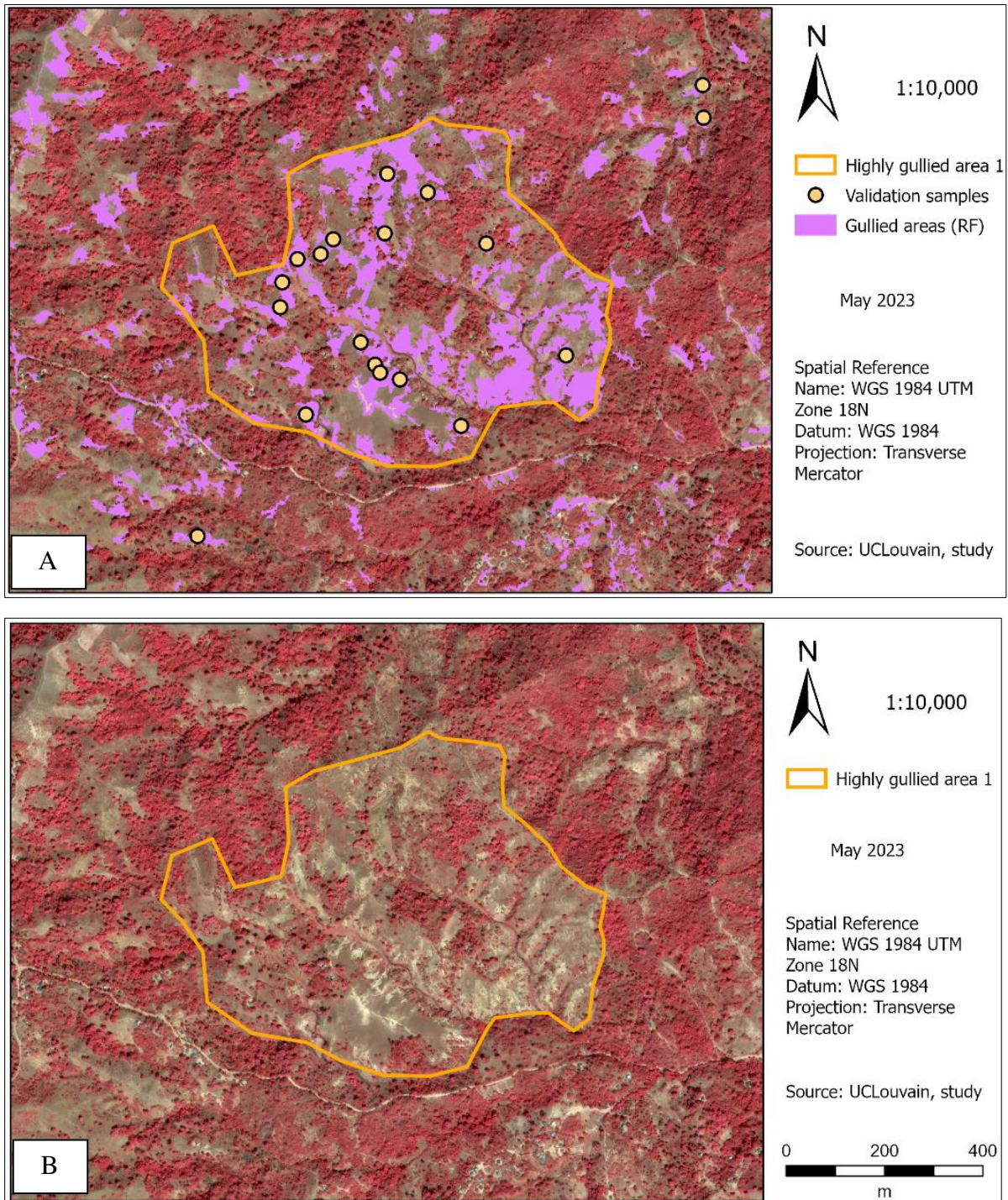
Table 4.4: Ranking (importance) of the 25 features involved in the object-based classification using Gini index

Rank	feature	Gini index	Feature #	Domain
1	Mean_NDVI	0.1348	16	Spectral
2	Mean_SAVI	0.1196	14	Spectral
3	Mean_Red	0.1065	18	Spectral
4	Mean_NDSI	0.0946	15	Spectral
5	Max_diff	0.0929	10	Spectral
6	STD Green	0.0553	22	Spectral
7	STD NIR	0.0514	24	Spectral
8	Mean_Green	0.0489	13	Spectral
9	STD NDVI	0.0435	23	Spectral
10	Mean_Blue	0.0415	11	Spectral
11	Brightness	0.0409	2	Spectral
12	Mean_NIR	0.0293	17	Spectral
13	GLCM_Homogeneity	0.0268	7	Textural
14	Density	0.0182	4	Geometric
15	Length/Width	0.0129	9	Geometric
16	Shape_index	0.0122	21	Geometric
17	Area	0.0121	0	Geometric
18	Asymmetry	0.0119	1	Geometric
19	Compactness	0.0086	3	Geometric
20	Rectangular fit	0.0076	20	Geometric
21	GLDV_Entropy	0.0070	8	Textural
22	GLCM_Entropy	0.0065	6	Textural
23	Mean_DEM	0.0063	12	Thematic
24	Mean_Slope	0.0053	19	Thematic
25	GLCM_Contrast	0.0052	5	Textural

4.2.4. Binary classification

Following the previous step, a binary classification was performed using the two classifiers. The eroded area was defined as one class, and all other classes were merged into the non-eroded area class. This transformation does not modify the results obtained earlier. However, it provides a better visualization of predicted eroded areas compared to the original image (Figure 4.6) and to all non-eroded areas (Figure 4.7).

Figure 4.6 displays the extent of gullied areas with RF (A) and DT (C) and compared to the original image (B) in one the two high-density gully zones. It should be noted that this zone is in the ground truth area. Figure 4.7, on the other hand, shows the extent of gullied areas across the entire area of interest (106 km²) using Decision Trees (Figure 4.7 A) and Random Forest (Figure 4.7 B).



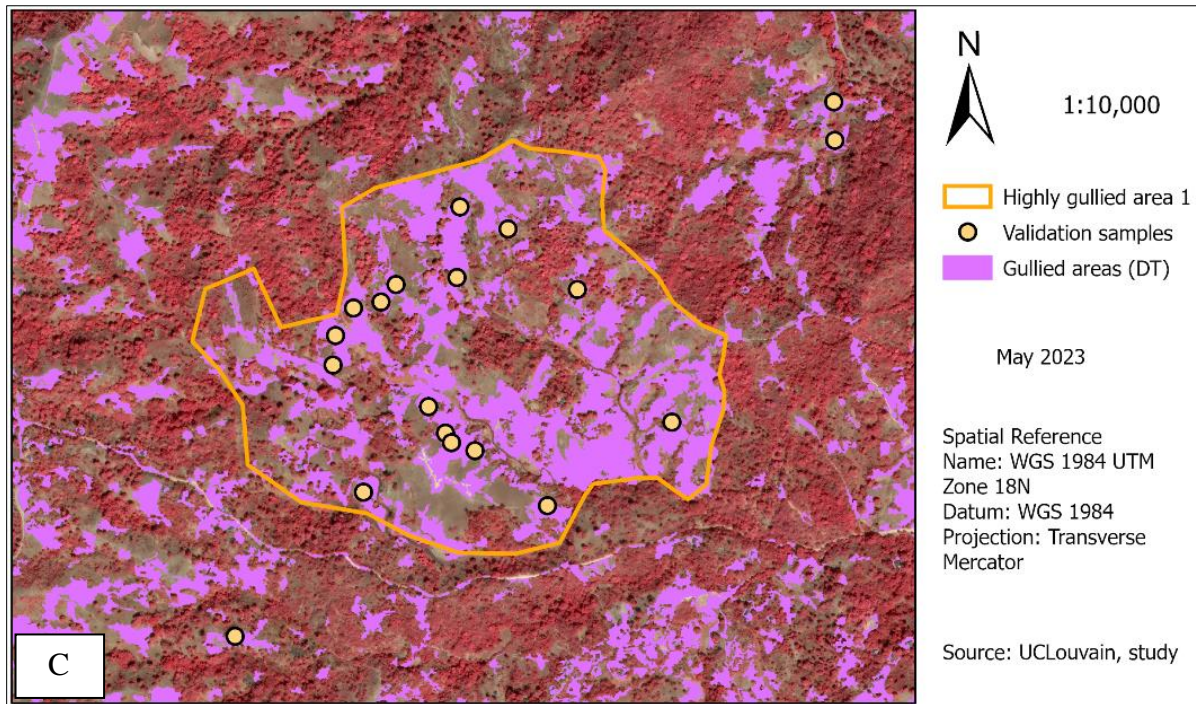


Figure 4.6: Binary classification between eroded and non-eroded areas with Random Forest (A) and Decision Trees (C). (B) is the False color IR of the original image

The total predicted highly eroded area with Decision Trees is estimated to be 9.1 km^2 , which is 8.5% of the total study area. The gullied area estimated with Random Forest is 3.4 km^2 , which is 3.2% of the study area. The gullied area predicted with Decision Trees is therefore nearly three times that of Random Forest. As mentioned earlier, this is due to the overestimation of objects in the "Eroded area" class originating from either the "Bare soil" class or the "Roads" class with Decision Trees.

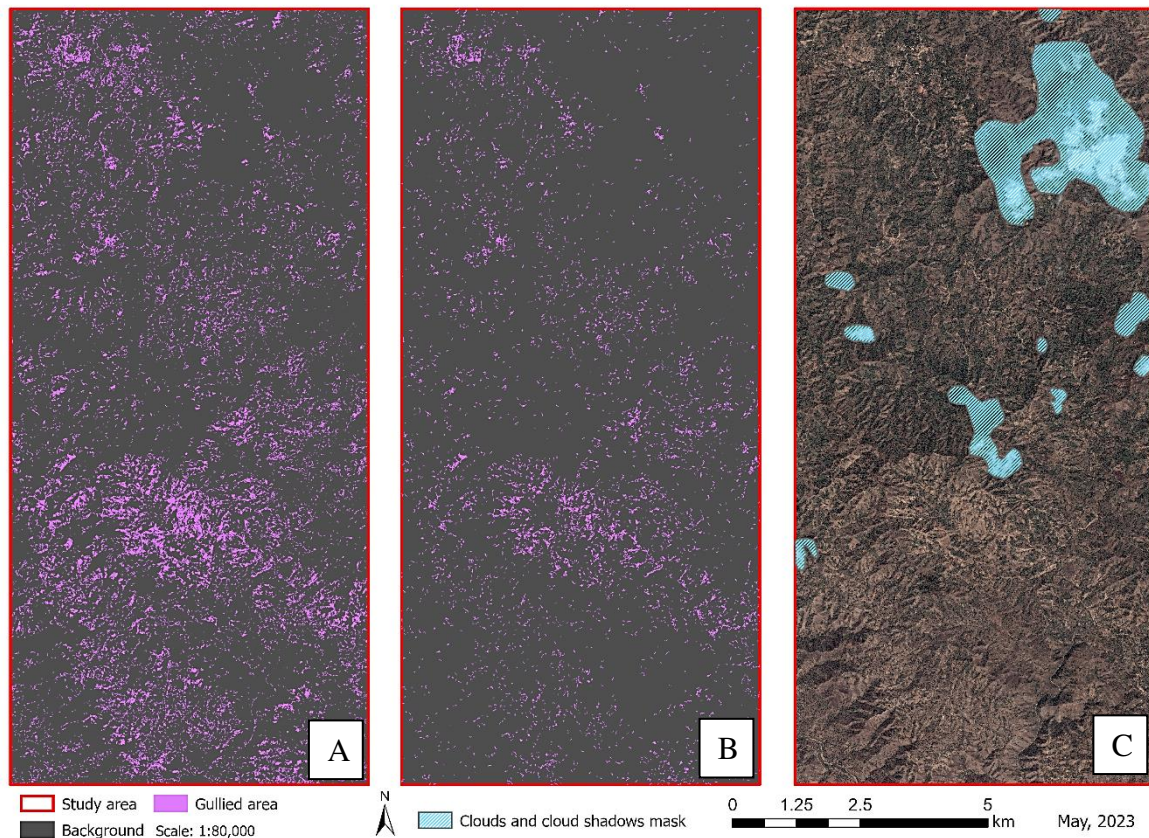


Figure 4.7: Prediction of gullied areas using Decision Trees (A) and Random Forest (B), and the original image with a mask for clouds and cloud shadows (C)

4.3. Statistical analysis of created objects

Liu et al. (2017) found that employing a well-designed segmentation strategy can significantly improve classification accuracy, resulting in a 5% increase in F-Score. In this respect, soil and vegetation indices play a crucial role in object segmentation, and visualizing these indices helps understand their impact on object formation. In this study, after the segmentation process, a total of 386,073 objects were created for the entire area of interest. An analysis of soil and vegetation indices was conducted for all objects and compared to data from objects in the "eroded area" class.

Considering Pléiades images are encoded on 12 bits, a wide range of brightness values is available for each channel. This allowed for the establishment of threshold values to accurately mask clouds (brightness value greater than 2200) and their shadows (brightness value lower

than 600). Although there may be land cover features with high brightness values, such as metallic roofs, their small size compared to the size of the objects they fall on has a negligible effect on the average brightness value of the surrounding objects.

Three important indices were calculated: NDVI, SAVI, and NDSI. For gullied areas, it was observed that SAVI had higher average values than NDVI, while their standard deviations were similar. The minimum and maximum values of NDSI were higher for gullied areas compared to the other indices, although the standard deviation was the same as NDVI. Table 4.5 shows statistics for three indices of the five main features used in RF classification and highlights the comparison of these indices between gully objects and overall objects. The maximum difference and the red reflectance complete the top five features used in the classification.

As expected, the NDVI and SAVI values are lower for gullied areas compared to the average of all objects. In contrast, the NDSI values were higher for gullied areas, indicating areas with generally low vegetation cover. These values can support further analysis based on expert knowledge in studying erosion in the Grande Rivière du Nord watershed.

Table 4.5: Basic statistics of the main features of the "eroded area" class and overall objects (excluding clouds and cloud shadows)

Indices	Object domain	Min	Max	Mean	Std
NDSI	Gully objects	0.21	0.33	0.26	0.02
	Overall objects	-0.42	0.56	0.098	0.078
NDVI	Gully objects	0.10	0.30	0.18	0.02
	Overall objects	-0.17	0.79	0.44	0.13
SAVI	Gully objects	0.12	0.36	0.21	0.03
	Overall objects	-0.20	0.95	0.53	0.16

4.4. DEM quality assessment

A Digital Elevation Model (DEM) refers to both Digital Surface Models (DSMs) and Digital Terrain Models (DTMs). The choice of DTM or DSM depends on the intended application. For

example, a DSM is more suitable for image orthorectification as it contains information on the elevation of buildings and trees. On the other hand, a DTM is necessary for hydrological modeling, which requires information about the ground level where surface water runoff occurs (Polidori and El Hage, 2020). In this study, a DTM was generated using three Pléiades panchromatic image scenes. The Agisoft Metashape Professional software used these images to produce a dense point cloud consisting of 187 million points. This point cloud was then interpolated to generate a 1-meter resolution DEM. A subset of the DEM and a zoomed-in view of a specific part of the ground truth area can be seen in Figure 4.8.

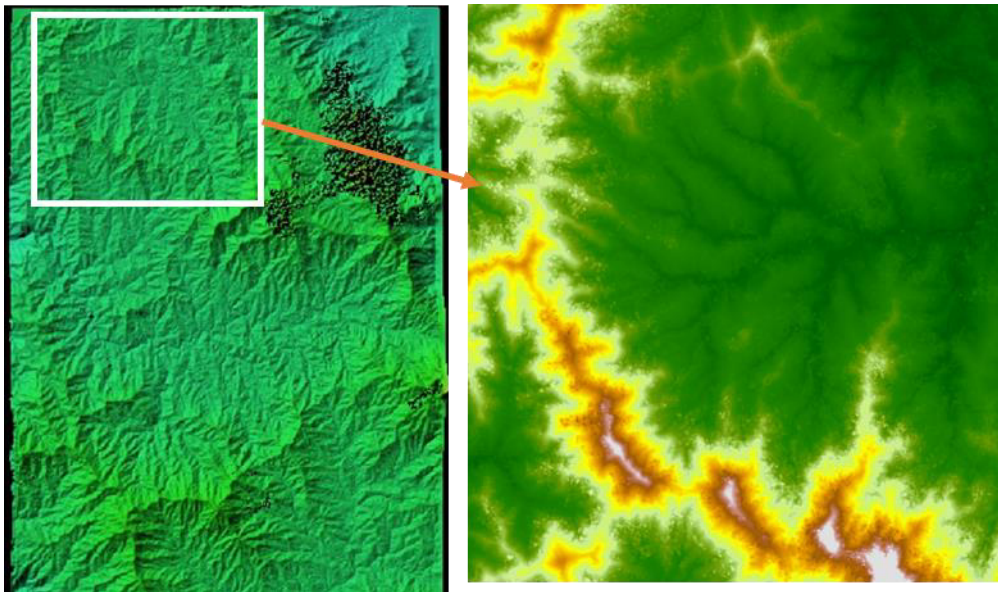


Figure 4.8: View of a subset of the generated DEM using Pléiades imagery (left) and a zoomed-in section (right)

It is necessary to assess the quality of the DEM to be useful for terrain analysis. Quality assessment of a DEM can be done with or without the use of external ground reference data, as shown by Betts and DeRose (1999). Without reference data, an internal quality assessment can be done using realistic criteria based on a priori knowledge.

In this study, we evaluated the quality of the DEM generated by comparing it with the CNIGS DTM using statistical analysis. We also plotted cross-sections resulting from a 300-m transect for both CNIGS DEM and the generated one.

4.4.1. Statistical analysis

This method involves using statistical indicators to compare the DEM with reference data or other DEMs to assess its quality and accuracy. Comparisons were made on a subset of 4.42 km² within the ground truth area.

Table 4.6: Comparison of elevation data between Pléiades and CNIGS DEM

Elevation	CNIGS	Pléiades	Difference
Min	306	262	44
Max	496	455	41
Mean	372	330	42
Standard dev.	34	34	0
Skewness	0.62	0.62	0
Kurtosis	2.84	2.87	0.03

For the studied subset, after co-registering the two DEMs by aligning them for overlapping areas, Table 4.6 shows a difference of 44 meters for the minimum altitude and 41 meters for the maximum altitude. This difference could potentially be attributed to interpolation issues, such as the presence of clouds, which may have affected the accuracy of the elevation values. A second possibility would be to verify that the RPCs provided with the images are correctly georeferenced, but this aspect falls outside the scope of this study. However, it is worth noting that despite the bias in elevation values, the distribution of altitude values appears to be similar for the two DEMs based on the other parameters presented in the table, including standard deviation, skewness, and kurtosis.

4.4.2. Profile analysis

A 300-meter transect was conducted to compare the two Digital Elevation Models (DEMs). The Pléiades DEM, with its higher resolution, exhibits greater variation along the transect, resulting in a more detailed representation of the terrain. On the other hand, the CNIGS DEM appears smoother, possibly due to a coarser resolution. Additionally, an average altimetric difference of 42 meters is observed between the two DEMs. This observed value was utilized to adjust the

Pléiades DEM, ensuring effective overlapping and facilitating a more meaningful comparison between the two datasets.

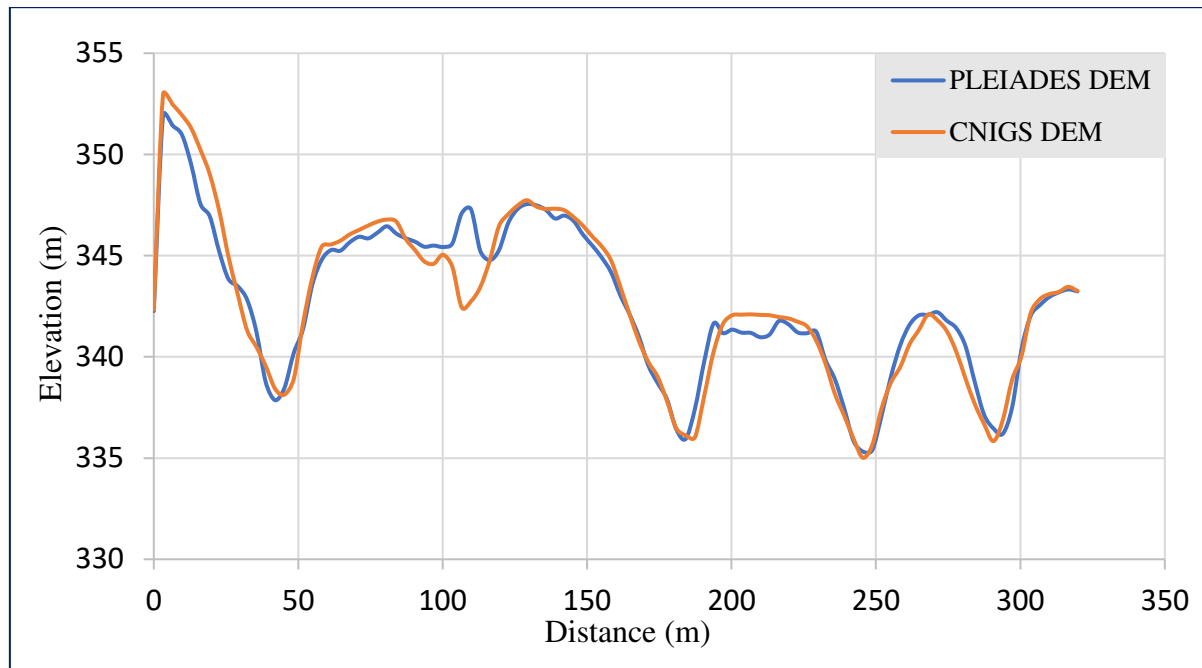


Figure 4.9: Profile comparison between the CNIGS DEM and the adjusted Pléiades DEM

The three depressions on the right (as example) constitute natural valley-bottoms. It can be observed that they are sufficiently close in both models. However, a small discrepancy can be observed at around a hundred meters (Figure 4.9). There are still some improvements needed before the DEM can be usable. This aspect of the research can be further developed in a future study. Nevertheless, this study highlighted the potential of Pléiades images for DEM generation in Haiti, particularly for Grande Rivière du Nord watershed.

4.5. Valley-bottom gullies

During the field survey, we compiled and analyzed a dataset consisting of 166 valley-bottom gullies. We collected information such as the geolocation of the gullies, their dimensions (base width, estimated depth, and width at the top), as well as an estimation of vegetation cover and erosion level. Erosion level and vegetation cover were classified into three categories: low, moderate, and high. The average bottom-width of the gullies was found to be **6.45** m, with a maximum value of **19** m. Analysis of the data revealed a correlation of **-0.32** between erosion

level and vegetation cover. This negative number means that as vegetation cover decreases, the erosion level tends to increase, and vice versa. This value also suggests a moderate but significant correlation between erosion level and vegetation cover. However, it is crucial to consider the contextual factors surrounding these findings. Terrain conditions can evolve over time, and the estimation of vegetation cover and erosion levels relied on subjective visual assessments, which are constrained to specific locations. Therefore, caution should be exercised when interpreting these results.

5. DISCUSSIONS

5.1. Gully erosion mapping

The eCognition software remains an indispensable tool for segmenting images and mapping areas affected by gully erosion, as documented in numerous studies (Liu et al., 2018; Shahabi et al., 2019; Shruthi et al., 2011). It enables images to be classified both by object and by pixel, providing greater flexibility and accuracy in identifying gullied areas. OBIA has indeed become a widely used approach for image classification and feature detection, particularly for gullies in different geographic contexts (d'Oleire-Oltmanns et al., 2014; Karami et al., 2015). This is because OBIA not only utilizes reflectance information, but also incorporates spatial topology to better represent actual terrestrial features. By analyzing and grouping objects based on their size, shape, texture, and context, OBIA can effectively distinguish and classify features such as gullies, leading to more accurate and reliable results.

To ensure optimal segmentation, two vegetation indices and one soil index were integrated into the workflow, thereby enabling better discrimination of gullies from surrounding features. Additionally, elevation data were incorporated to improve the classification of gullied areas which often exhibit similar reflectance patterns to bare soils, roads, and building footprints. Indeed, gullies typically exhibit significant variations in elevation compared to the surrounding areas. By introducing elevation data, it is possible to identify homogeneous zones based on distinctive topographic characteristics of gullies. Over-segmentation was prioritized but controlled to avoid an excessive number of objects, given the resolution and size of the image used. Overall, the eCognition software represents a powerful tool for gully mapping using the object-based approach.

5.2. Pléiades images in gully erosion study

The developed approach for gully mapping relies on the use of multispectral images. Firstly, it involves computing indices, which are crucial in delineating features. Secondly, pan-sharpened image data allows for a higher resolution of up to 50 cm and better integration of contextual information such as spatial topology and textural features. Finally, the three panchromatic scenes were used to create a DEM. Elevation data are generally important in gully mapping.

However, the elevation and slope derived from the DEM were of lesser importance in the classification. A DEM with higher elevation resolution could yield better results.

Although some authors suggest that good accuracy can be achieved without a DEM (d'Oleire-Oltmanns et al., 2014), others believe that 3D information should be considered. On one hand, surface conditions like vegetation can affect the imagery, making it difficult to distinguish gully from non-gully areas using only imagery-derived features (Liu et al., 2017). On the other hand, since image quality varies in time (due to seasonal effects and weather conditions) and space (due to cloud for example), features based solely on multispectral images may be less useful in classification tasks.

Since the DEM generated from Pléiades data was not entirely consistent with the CNIGS one, the latter was used in both segmentation and classification tasks. However, due to the size and depth of the gullies, having a DEM with higher resolution would be essential to better delineate isolated gullies on hillslopes. Ultimately, the DEM was found to be more useful in segmentation than in classification.

5.3. Random Forest classification

5.3.1. Multi-label classification analysis

In chapter four, Decision Trees and Random Forest were used to map gully erosion in the Grande Rivière du Nord watershed. Random Forest shows better overall results than Decision Trees. This is normal since Random Forest is an improvement of Decision Trees. It uses several decision trees to improve prediction accuracy by using a random subset of the training data. Additionally, Random Forest can handle large amounts of data, which is often required for image classification tasks. Therefore, due to its ability to effectively handle complex data and reduce bias and variance, Random Forest often generates better results than Decision Trees.

However, an analysis of the values from the confusion matrix (Table 4.3) shows that for Random Forest model, the confusion of gullies in relation to "bare soil" and "low vegetation" is much higher than for objects in other classes. This is due to two reasons: firstly, these data are based solely on expert interpretation, and secondly, they can have similar reflectance values. The "Road" class is less confusing for the model partly because of the geometry of these objects.

Due to the dispersion and size of buildings in the landscape, the built-up class is poorly represented in areas of low density. The “rectangular fit” feature should have helped, but it hadn’t because the size of the houses is often significantly smaller than that of their surrounding objects. They are probably classified as bare soil because houses often have a courtyard that is bare and larger than the house itself. These houses also have extreme reflectance levels due to the nature of the roof and its novelty. To a lesser extent, the low number of data can explain the low precision of the “Bare soil” and “Built-up” classes.

For both models, the Producer Accuracy and User Accuracy reached the maximum value of 100% for the “Forest” class. This means that all objects in this class are correctly classified with respect to reference data and the map respectively. The two models therefore show maximum performance in classifying objects with high NDVI values. This impressive result is linked to NDVI thresholding, which ensures that calibration samples in the "forest" class are optimal.

5.3.2. Random Forest binary classification

As Random Forest showed better performance, we studied the results of this classifier in detail. In this binary classification, the results for the “Eroded area” class remain the same. However, all the other classes were merged into a single superclass that includes all non-gully objects.

Out of the 32 validation objects in “severely eroded class”, 29 were correctly detected and defined as true positives. Three False Negatives and two False Positives were identified. This means that two objects identified as gullies are not actually present as such in the field, while three gully objects in the field were identified on the map as belonging to non-gullies. These values are reversed for the class of non-gully objects. The result is an identical F-score of 0.92 for both gullied areas and non-gullied areas. The three false negatives come from the "Bare soil" and "Builtup" classes, while the two false positives are in the "Roads" class. This can be explained by the reflectance of all these classes, which may be similar or very close. F-score result is a unique measure of model performance that considers both false positives and false negatives.

Although the results can still be improved by finding a compromise between the number of variables and the number of trees to impose on the model, they are quite satisfactory compared to similar studies on gully mapping. For example, Shahabi et al. (2019) achieved a precision of

81% and an F-score of 85% in large-scale mapping of gully-affected areas using Sentinel 2A images. D'Oleire-Oltmanns et al. (2014) used high-resolution Quickbird-2 satellite images for the detection of gully-affected areas in Morocco and found an overall accuracy of 62%, with 16% of commission error and 38% of omission error. The conditions of these studies are not entirely identical to ours, but we can state that the applied methodology secure good results.

To our knowledge, no study related to gully detection using remote sensing has been found in the local context, and particularly not for the object-oriented method. Therefore, the validity of the results can only be measured based on studies carried out in other areas with different contexts. This study also reveals the importance of having an erosion inventory map to validate future studies and lay the foundations for monitoring gully erosion in Haiti.

5.3.3. Features importance for Random Forest

It is important to determine the optimal number of features to use during classification to achieve accurate predictions. Breiman (2001) suggested that if the number of features is too small, the number of trees becomes too large, leading to increased error. Similarly, if the number of features is too high, their mutual correlation increases, resulting in higher error rates. Therefore, feature importance was determined, with vegetation and soil indices ranking highest. Combined SAVI and NDSI indices provided better delineation between bare areas with low or sparse vegetation and completely eroded areas with no vegetation. We found that red reflectance achieved better score than blue and green.

Texture indices, including homogeneity, entropy, and contrast, were calculated based on flow direction. Only homogeneity was among the 12 most important features, while the others had a lesser contribution to classification (Table 4.4). This could be attributed, on one hand, to a scale factor between the multispectral image (0.50 m), and the flow direction layer (1.5 m). On the other hand, the altimetric resolution of the DEM is 1 meter, which does not allow for accurate representation of texture for gullies with a similar depth scale. A solution would be to calculate textures based on SAVI or NDVI, as suggested by Laliberte et al. (2007), or to use a DEM with higher resolution than the one used in this study, closer to that of the image. Quantifying the importance of variables is crucial not only for ranking them before using a stepwise estimation model but also for interpreting data and understanding underlying phenomena in many applied

problems (Genuer et al., 2010). However, the challenge that remains is to determine a suitable threshold for selecting which variables to retain for optimal classification.

5.3.4. Level of erosion targeted

In this research, only areas with severe erosion (only highly gullied areas) were targeted to be detected. This was to ensure the accuracy of the calibration data based solely on image interpretation. With Random Forest, the results indicate that 3.2% of the studied is severely eroded. Although this percentage may initially appear low, visual observations and analysis reveal that two specific regions are significantly impacted by gully erosion, with one of them experiencing over 50% degradation. Thus, assuming a balance between false positives and false negatives segments, the erosion rate and therefore the effective eroded area will be greater than the actual value of 3.2%.

5.4. Replicability of the proposed method

To replicate the proposed method, two key factors must be considered: the nature and source of the images, as well as the spatial correlation. This study demonstrates that Pléiades images can be used to map gully erosion in Haiti. However, multispectral images are often affected by clouds, especially in regions near the equator like Haiti. Therefore, acquiring the images, which are also costly, must be done during a period when cloud coverage is minimal, preferably in the dry season.

Before the field visit, the Sainte-Suzanne municipality was chosen as the region of interest due to its similarity and representativeness for the watershed of the Grande Rivière du Nord. The topography, including the average slope, vegetation cover, and soil types, were similar at both scales. Moreover, the detection of gully erosion was conducted over an area of no less than 106 km², or nearly 1/6 of the total watershed area. The object-oriented approach developed in this study is entirely transferable and can be applied to other areas outside of the studied watershed. However, due to the spatial variability of the Haitian terrain, recalibration will certainly be necessary to obtain optimal objects following segmentation for any other area. Overall, this study provides valuable insights into the use of remote sensing data for mapping gully erosion in Haiti. It highlights the importance of careful image selection, as well as the need to consider spatial correlation and terrain variability when using object-oriented approaches.

6. CONCLUSION AND PERSPECTIVES

Gully erosion is known as a major land degradation, particularly in the Grande Rivière du Nord watershed in Haiti. This form of water erosion is responsible for soil loss, infrastructure damage, and water pollution. To detect gully erosion in the watershed, an object-based approach and machine learning algorithms were used in this study. The proposed methodology involved a calibration step to find optimal parameters for better delineation of gully-affected areas. Spectral indices and elevation data were used in addition to basic homogeneity criteria to enhance the segmentation. The study area covered 106 km² and a land-cover classification was performed using both Decision Trees and Random Forest. The accuracy of the classification was checked using a confusion matrix, and results indicate that the Random Forest classifier provide better results than Decision Trees. Results also indicate that 3.2% of the studied area exhibit severe erosion. Although this percentage may initially appear low, further analysis and visual observations reveal that two specific regions are significantly impacted by gully erosion, with one of them experiencing over 50% degradation. In addition, only highly gullied areas were studied. Thus, assuming a balance between false positives and false negatives segments, the erosion rate and therefore the degraded area will be greater than the actual value of 3.2%.

The accuracy assessment of the RF classification demonstrates an overall accuracy of 0.86 and an impressive F-score value of 0.92 for gullied areas. When compared to similar studies, these findings provide relevant and valuable insights. The developed approach can be extended and applied to the whole study area, and the results can be used for soil conservation and land management purposes. Although land cover such as roads and bare soil were initially difficult to handle when visually analyzed in images, this issue was overcome with the developed approach. However, due to the variability in terms of degradation level, vegetation cover, bank nature, and soil type, the method may need some adaptations before it can be transferred to other regions. We therefore suggest the following:

1. Ordering Pléiades images at least at the end of the year can ensure that they are available during the dry season when cloud cover is minimal. It is greatly recommended that valley-bottom gullies prone to land management should be deeply investigated, considering the variability and complexity of the factors that influence their evolution.

2. Calculation of texture using flow direction did not yield significant results in the classification process. This could be attributed to the resolution limitations of the DEM, with a vertical accuracy of 1 meter and a horizontal accuracy of 1.5 meters. It is worth exploring the possibility of calculating texture based on a vegetation index such as SAVI in future studies, as this may lead to improved results. A promising alternative would be to integrate LiDAR data to obtain an accurate representation of the terrain. LiDAR data can generate a highly precise DEM of the land surface, by providing more detailed information on the structure and roughness of the terrain.
3. Initially, this study focused on gullies located in valley-bottoms. As a result, there was limited availability of reference data (ground truth data) specifically for gullied areas, on hillslopes. For other land cover classes, the data originate exclusively from image interpretation. Therefore, it is crucial to gather much more field data to ensure a more representative validation for future research related to the study area.
4. Furthermore, it is highly recommended to develop an inventory map specifically for gully erosion. This will facilitate ongoing monitoring efforts to assess the expansion of this phenomenon within the Grande Rivière du Nord watershed and, more broadly, in Haiti. Additionally, measures should be implemented to address uncontrolled deforestation and the adoption of erosive agricultural practices, both of which were observed during the field visit.
5. In the future, we suggest considering the use of CNNs for mapping valley-bottom gullies. CNNs can learn and adapt in environments with significant spatial variability, making them potentially valuable tools for investigating environmental phenomena in Haiti.

By implementing these suggestions, future studies can provide more accurate and comprehensive insights into gully erosion, contributing to better management and conservation practices in the Grande Rivière du Nord watershed.

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ANNEXES

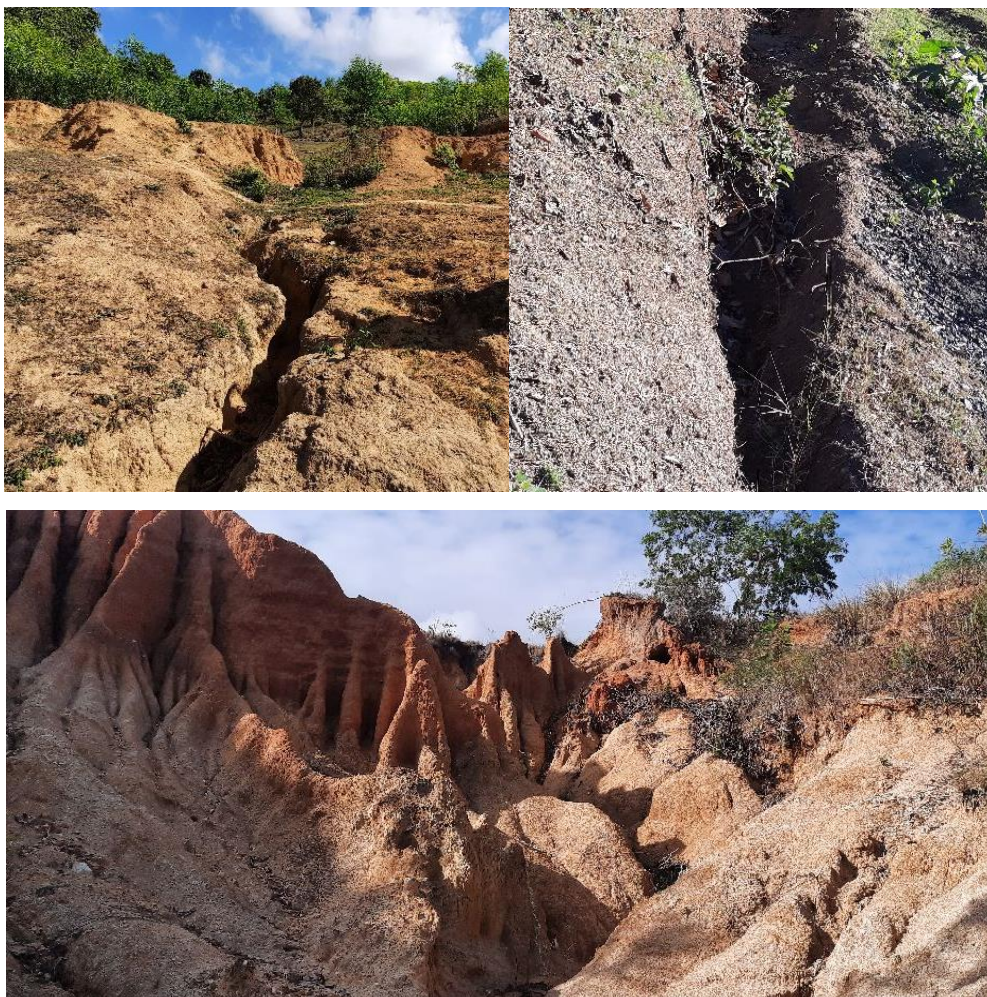
Annex A: Terrestrial view of large valley-bottom gullies and bed erosion observation



Annex B: Hillslope gullies (A) and large valley-bottom gullies (B) in aerial photographs, Sainte-Suzanne



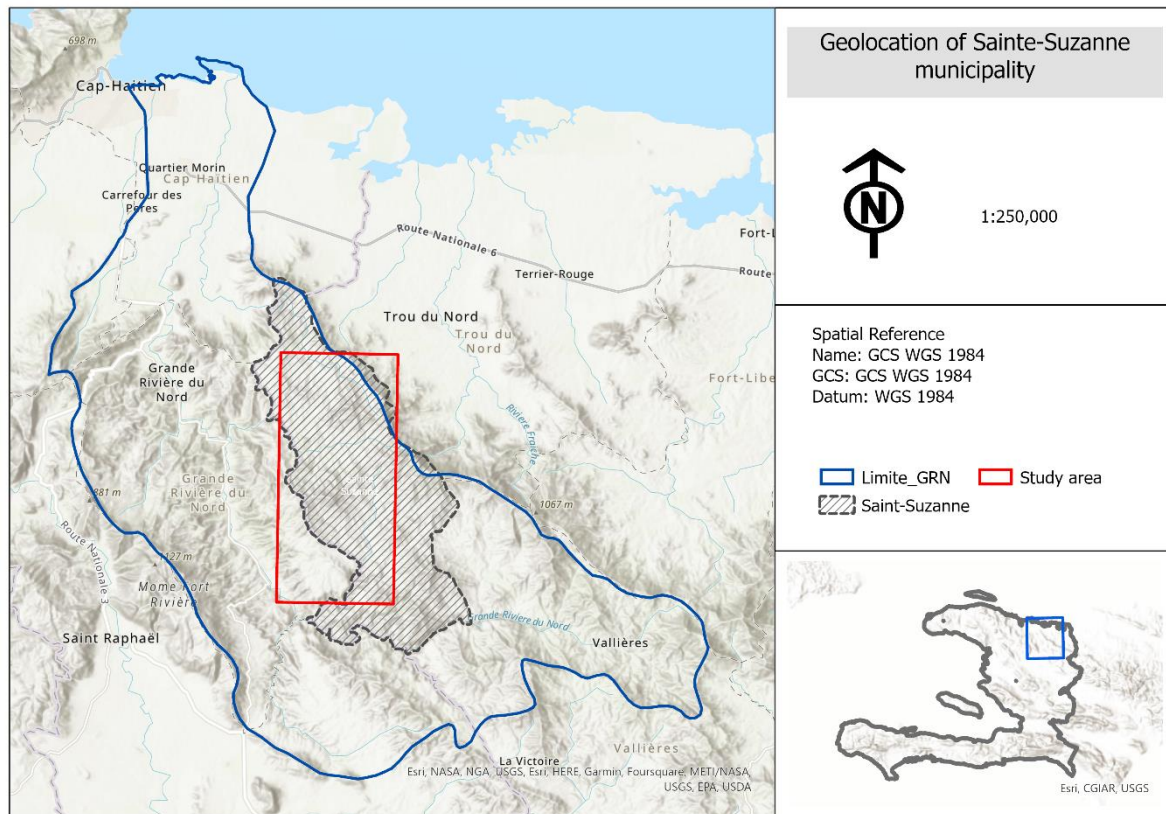
Annex C: Terrestrial observation of gully erosion on the hillslopes



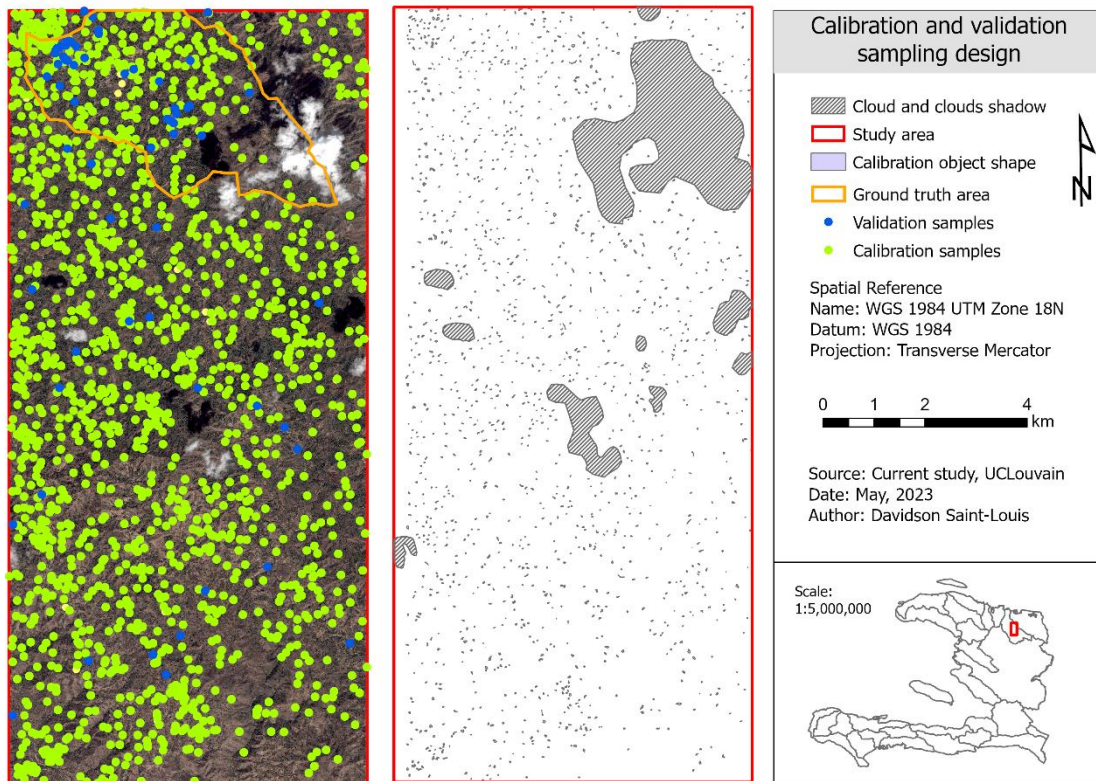
Annex D: Highly gullied area (A) and moderately gullied area (B)



Annex E: Geolocation of Sainte-Suzanne municipality



Annex F. Sampling plan for calibration and validation data



Annex G: Python Script for calibration and validation data split

```
import geopandas as gpd
import pandas as pd
import numpy as np

# Nb données de validation aléatoires à extraire pour chaque classe
n_validation_par_classe = {
    'Eroded_area' : 32,
    'Bare_soil': 6,
    'Builtup': 6,
    'Roads': 6,
    'Low_vegetation': 7,
    'Forest': 7
}

# Nom du fichier shape contenant les données
nom_fichier = '/content/data/data part a.shp'

# Lecture du fichier shape en utilisant GeoPandas
donnees = gpd.read_file(nom_fichier)

# Séparation des données par classe
donnees_par_classe = donnees.groupby('Class')

# Initialisation des listes pour stocker les données de validation et de
# calibration
donnees_validation = []
donnees_calibration = []

# Extraction des données de validation et de calibration pour chaque classe
for classe, data in donnees_par_classe:
    n_validation = n_validation_par_classe[classe]
    if len(data) >= n_validation:
        # Sélection aléatoire de n_validation enregistrements pour la validation
        indices_validation = np.random.choice(data.index, size=n_validation, replace=False)
        donnees_validation.append(data.loc[indices_validation])
        donnees_calibration.append(data.drop(indices_validation))
    else:
        # Si le nombre d'enregistrements dans la classe est inférieur au
        # nombre d'enregistrements
```

```
        # demandé pour la validation, tous les enregistrements sont mis
dans le fichier de calibration
        donnees_calibration.append(data)

# Concaténation des données de validation et de calibration pour chaque
classe
donnees_validation = pd.concat(donnees_validation)
donnees_calibration = pd.concat(donnees_calibration)

# Écriture des fichiers de validation et de calibration
donnees_validation.to_file('/content/data/validation_.shp')
donnees_calibration.to_file('/content/data/calibration_.shp')
```

Annex H: Python script for the accuracy assessment

```
import pandas as pd
from sklearn.metrics import confusion_matrix, accuracy_score
import pandas as pd
from sklearn.metrics import classification_report
import io

# Charger les données à partir du fichier CSV
data = pd.read_csv('/content/Assessment.csv')

# Extraire les colonnes de données prédites et de validation (ground truth)
y_pred = data['Assigned_c'] #colonne prédite
y_true = data['Class'] #colonne ground truth

# Créer une matrice de confusion
cm = confusion_matrix(y_true, y_pred)

# Calculer l'exactitude
accuracy = accuracy_score(y_true, y_pred)

# Créer une matrice de confusion détaillée
report = classification_report(y_true, y_pred)
print(report)

# Générer le rapport
report = classification_report(y_true, y_pred)

# Convertir le rapport en objet StringIO
report_obj = io.StringIO(report)

# Lire l'objet StringIO dans un DataFrame
df = pd.read_csv(report_obj, sep='\s+')

# Sauvegarder le DataFrame dans un fichier CSV
df.to_csv('/content/Rapport_accuracy.csv', index=False)
```

Annex I: Python script for Gini index computation in the classification with Random Forest

```
from sklearn.ensemble import RandomForestClassifier
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd

# Load the dataset
classes = pd.read_csv("/content/Classes.csv")
classes = np.array(classes)

features = pd.read_csv("/content/Features.csv")
features = np.array(features)

X, y = features, classes

# Train a Random Forest classifier
rfc = RandomForestClassifier(n_estimators=100, random_state=42)
rfc.fit(X, y)

# Compute the feature importances using the Gini index
importances = rfc.feature_importances_
indices = np.argsort(importances)[::-1]

# Print the feature ranking
print("Feature ranking:")
for f in range(X.shape[1]):
    print("%d. feature %d (%f)" % (f + 1, indices[f], importances[indices[f]]))

# Plot the feature importances
plt.figure()
plt.title("Feature importances")
plt.bar(range(X.shape[1]), importances[indices], color="gray", align="center")
plt.xticks(range(X.shape[1]), indices)
plt.xlim([-1, X.shape[1]])
plt.xlabel("Features")
plt.ylabel("Importance")
plt.show()
```

Annex J: Haralick texture using Orfeo ToolBox

```
otbcli_HaralickTextureExtraction -in  
/export/homes/students/saintlouis/Image/flow_direction.tif -channel 1 -parameters.xrad 3 -  
parameters.yrad 3 -texture simple -out  
/export/homes/students/saintlouis/Image/flow_direction_texture.tif?gdal:co:TILED=YESand  
gdal:co:COMPRESS=LZW'
```

channel 1	number of bands [gray level intensity ranges from 0 to 255]
xrad, yrad = 3	patch size
in	path and name of the input image
out	path and name of the output image

CHARACTERIZATION OF GULLY EROSION BY REMOTE SENSING IN HAITI: THE CASE OF THE GRANDE RIVIÈRE DU NORD WATERSHED

Gully erosion is a widespread form of land degradation throughout the world. In Haiti, it is primarily driven by deforestation and erosive farming practices. Natural factors such as heavy rainfall, rugged terrain, and soil characteristics further exacerbate gully erosion process. Gully erosion results in significant soil loss and increased transported sediment load, which has a negative impact on soil quality and causes damage to downstream infrastructures. Therefore, accurate mapping of gullied areas is crucial for erosion mapping, monitoring, and control, particularly in the Grande Rivière du Nord watershed, which is highly susceptible to water erosion.

In this study, an object-based approach was developed to map gully-affected areas in the Grande Rivière du Nord watershed using high-resolution Pléiades satellite imagery. The methodology involved data preparation, a field survey in Haiti, and remote sensing data processing. Various metrics such as spectral indices (NDVI, SAVI, NDSI) and elevation-derived data were computed using eCognition software. Image segmentation was performed using a scale parameter of 100, combined with shape (0.7), compactness (0.5), and spectral indices.

For object-based image classification, both Decision Trees (DT) and Random Forest (RF) models were used. The results showed that the RF model outperformed the DT model in terms of overall accuracy (86%), precision (94%), and F-score (92%). The estimated extent of gullied areas using RF was 3.4 km², corresponding to 3.2% of the total study area of 106 km². Spectral indices were found to be the most influential features for gully mapping, followed by shape features and the textural homogeneity index. Elevation data were useful in image segmentation but did not contribute significantly to classification results.

By combining field surveys and remote sensing data acquisition, the approach developed can be replicated for mapping gully erosion in the Grande Rivière du Nord watershed. However, it may need to be adapted before application in other regions. The results highlight the importance of remote sensing data and object-based analysis for accurate gully mapping in Haiti, providing valuable information for erosion monitoring and management.

Keywords: Gully erosion, Haiti, machine learning, object-based image analysis, accuracy

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