

Mapping and understanding farmers' responses to gully-induced problems in the Abaya-Chamo Sub-Basin, Southern Ethiopia

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ABSTRACT

Gully erosion threatens the livelihoods of rural farmers by causing direct cropland loss and reducing agricultural productivity. In the Shafe catchment of southern Ethiopia, smallholder farmers facing severe food insecurity have implemented gully interventions (GIs) to counter this land degradation. Yet the spatial distribution of these GIs remains highly uneven. This study investigates which GIs have been implemented, what drives their adoption, and whether this adoption has spread as a diffusion process over time.

To investigate GI adoption, fieldwork was conducted across two rural administrative units in the Shafe catchment. GI presence was mapped for 751 gullies based on field observations and drone surveys. Additionally, a household survey of 178 farmers was conducted, providing socio-economic and perceptual data of the farmers, their plots and their gullies. Variables were tested through univariate screening and logistic regression models. Finally, spatial clustering and spatio-temporal modelling were used to investigate the adoption of GIs over time.

Results indicate that GIs in the Shafe catchment are dominated by loose rock check dams and banana plantations. Conservation and economic motivations drive farmers to combine these interventions, since they promote gully stabilisation through sediment infilling while simultaneously creating additional agricultural opportunities on the gully floor. Field observations identified at least one GI in 18% of mapped gullies, with treated gullies being larger and located closer to roads and settlements.

The household survey, capturing individual farmer decisions across multiple gullies, suggests 48% of farmer-reported gullies have been treated at some point. Farmers across the study area share a broadly similar subsistence-oriented profile. With 88% of the farmers having implemented at least one GI somewhere on their land, motivation is near-universal. The central question is therefore not who adopts, but where: farmers preferentially treat gullies that are accessible, on productive plots close to the homestead, exclusively owned, and perceived as severely impacted. Adoption likelihood is slightly higher for farmers exclusively dependent on agriculture and those with sufficient economic surplus. Predictive models based on spatial variables and socio-economic variables provide a step towards a practical targeting framework.

This study also presents one of the first attempts to diffusion analysis for gully interventions. GI adoption shows significant spatial clustering. A weak but detectable diffusion effect suggesting that farmers are more likely to adopt GI when neighbouring farmers have done so in prior years, pointing to informal knowledge spreading. However, data limitations remain substantial and further research should confirm this with more complete data.

These findings highlight that the challenge in the Shafe catchment is not farmer motivation, but enabling adoption. Accordingly, support programmes should facilitate access to labour and materials, reinforce the dual conservation-production strategy already practised by farmers, and strategically target pioneer farmers to leverage potential diffusion effects.

LIST OF ABBREVIATIONS

AIC = Akaike Information Criterion

AMU = Arba Minch University

AUC = Area under the curve

CDF = Cumulative distribution function

CI = Confidence interval

DEM = Digital elevation model

GI = Gully intervention

GIS = Geographical information system

GPS = Global positioning system

IUC = Institutional University Cooperation

KDE = Kernel density estimation

KNN = K-nearest neighbours

N = Nitrogen

NGO = Non-governmental organisation

NIR = Near-infrared

OR = Odds ratio

PhD = Doctor of Philosophy

ROC = Receiver operating characteristic

QGIS = Quantum geographic information system

SWCM = Soil and water conservation measures

UAV = Unmanned aerial vehicle

VIF = Variance inflation factor

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CHAPTER 1

INTRODUCTION

Gully erosion is a process of land degradation in which soil is removed by significant amounts of concentrated runoff water, leading to the formation and expansion of large erosional channels (Poesen et al., 2003; Vanmaercke et al., 2021). Gully erosion can cause various on-site problems, such as direct loss of land, trees and crops, and damage to infrastructures, such as roads and buildings (Vanmaercke et al., 2021). In addition, gullies can affect the local hydrology. In dry environments this leads to significant lower crop yields around the gully edge (Frankl et al., 2016; Mekonnen et al., 2026; Vanmaercke et al., 2021). Furthermore, the development of gullies is associated with off-site problems, including the degradation of downstream waterways and increased sediment loads, reducing water quality (Imwangana et al., 2015; Poesen et al., 2003; Valentin et al., 2005; Vanmaercke et al., 2021). Given their often high erosion rates, gullies can account for 20–80% of average catchment sediment yield where they occur (Poesen et al., 2003; Vanmaercke et al., 2021). Occurring globally with varying degrees of severity across different regions, gully erosion forms a widespread environmental issue (Borja et al., 2018; Chen et al., 2026; Frankl et al., 2016; Valentin et al., 2005).

Gully erosion highly affects large parts of the African continent (Mekuria et al., 2024; Nyssen et al., 2004). Land use and land cover conditions are among the most important drivers of gully occurrence (Chen et al., 2026). This is especially pronounced in rural areas, where poverty-driven unsustainable land use practices combined with growing population pressure have allowed gullies to become widespread (Abeje et al., 2025; Chen et al., 2026). In this context, Ethiopia represents a well-known hotspot of gully erosion (Chen et al., 2026), posing a serious threat to agricultural productivity and rural livelihoods (Abeje et al., 2025). The economic costs associated with gully-induced soil loss are substantial (Mekonnen et al., 2026), further compounding the vulnerability of already marginalized farming communities (Ayele et al., 2015).

The Abaya-Chamo sub-basin in southern Ethiopia is severely affected by gully erosion (Belayneh et al., 2022; Mekonnen et al., 2026). Within this sub-basin, the Shafe catchment is among the areas most severely affected by erosion in the region (Abeje et al., 2025, Figure 1). Recent research by Mekonnen et al. (2026) directly quantifies the consequences for farming households: plots affected by gullies lose on average 54.3% of their effective crop yield. This results from a combination of direct cropland loss through gully widening, and gully-related effects in bordering fields, like soil moisture stress and reduced plant density. The loss of crop yield translates to an estimated 13.8% reduction in annual household income (Mekonnen et

al., 2026). Given that in the Gamo zone, where the Shafe catchment is located, 93-95% of households depend on subsistence farming as their primary livelihood and experience some form of food insecurity (Cholo et al., 2019), these losses are far from trivial.

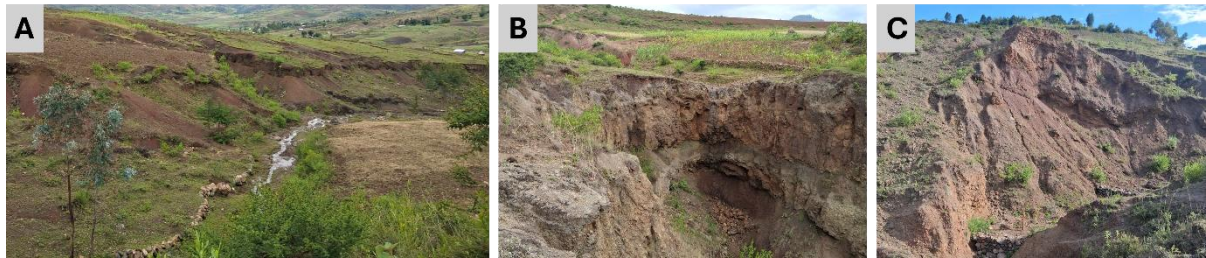


Figure 1: Gully erosion in the Shafe catchment, southern Ethiopia. (A) Gully system cutting through agricultural plots. (B) Close-up of an active gully headcut (C) Close-up of gully vertical walls illustrating lateral widening. Photos by author, [August 2025].

Several studies indicate that implementing gully interventions (GIs) can help prevent on- and off-site effects of gully erosion (Ayele et al., 2015; Frankl et al., 2021; Valentin et al., 2005). Numerous GIs have been implemented across the Shafe catchment. Yet, their distribution remains highly uneven (Abeje et al., 2025). What drives this variability in GI adoption by farmers remains poorly understood, despite its direct implications for food security and sustainable land management.

1.1 Defining a gully and its controlling factors

In literature, gullies are discussed under different names or local terms (e.g. *arroyos*, *dongas*, *ravines*, or '*borebor*' in the study area), and no official universally agreed definition exists (Thwaites et al., 2022). A key distinction is made between ephemeral gullies, which reform seasonally in cultivated land after being removed by tillage, and permanent gullies, which are persistent landforms that expand through headcut erosion (gully migrates upstream) and wall collapse (gully widening) and cannot be removed by tillage (Thwaites et al., 2022).

Several criteria are commonly used to distinguish gullies from smaller (rills) and larger (stream channels) erosional features (Poesen et al., 2003; Thwaites et al., 2022). At the lower boundary, a critical cross-sectional area of 929 cm² (i.e. 1 square foot) is commonly used as the threshold below which channels can still be removed by normal tillage (Poesen et al., 2003). Alternatively, a minimum depth of approximately 0.5 m is sometimes used (Poesen et al., 2003). Additionally, gullies are characterised by the presence of a headcut and an autochthonous sediment source, meaning that erosion occurs within the system itself, unlike stream channels, where sediment originates primarily from outside the incision system (Figure 2; Thwaites et al., 2022). The gullies studied here are permanent in nature, given their scale, depth, and multi-decadal persistence in the landscape (Belayneh et al., 2022; Mekonnen et al., 2026). An operational definition used for mapping purposes is provided in Section 2.2.2.

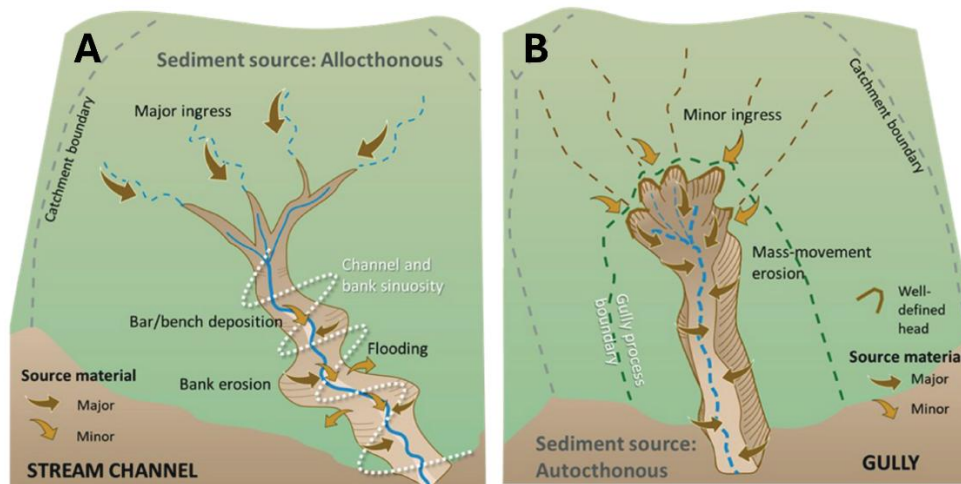


Figure 2: Schematic illustration of the differentiation between (A) gullies and (B) stream channels. Figure taken from Thwaites et al. (2022).

Research has identified topographic characteristics as key drivers of gully development, particularly gully slope and the size of the upslope drainage area (Vanmaercke et al., 2021). Once a gully has formed, gully wall height and slope influence wall stability, making gullies more susceptible to further collapse and retreat. Expansion rates tend to be highest in the early stages of gully development, before gradually stabilising over time (Vanmaercke et al., 2016). Beyond topography, climatic characteristics play an important role, as rainfall intensity strongly correlates with gully headcut retreat rates (Vanmaercke et al., 2016). Soil characteristics further affect gully dynamics, with soil texture, organic carbon content, coarse fragment content, water holding capacity, and susceptibility to piping all contributing to increased erosion rates (Vanmaercke et al., 2021). In the Shafe catchment specifically, gully erosion is especially driven by lateral widening (Belayneh et al., 2022; Mekonnen et al., 2026).

Taken together these topographic, climatic and soil characteristics determine the overall severity of gully erosion, and can moreover increase the likelihood of structural failures of GIs (Frankl et al., 2021).

1.2 Gully interventions

Taking measures against gully erosion is a challenge (Amiri et al., 2019; Frankl et al., 2021; Poesen et al., 2003). The broader term soil water conservation measures (SWCMs), often discussed within the broader framework of soil erosion (Nigussie et al., 2017; Tesfaye et al., 2014a), encompasses interventions both within and beyond the gully itself. This study focuses specifically on interventions occurring inside the gully, referred to as gully interventions (GIs). These GIs can serve different objectives: some are explicitly aimed at stabilizing the gully and potentially reducing its size, referred to as gully control measures. Others are primarily

motivated by agricultural cropping, aiming to use the gully floor as productive land. While literature on gully control typically focuses on the former (e.g. Frankl et al., 2021; Vanmaercke et al., 2021), the latter was also frequently observed in the study area (De Bleser, 2025).

Several GIs are discussed in literature, including runoff diversion, gully reshaping, vegetation growth and check dams (Frankl et al., 2021; Reubens, 2010). Since 1980, better land use and conservation have been promoted for gully control in the Ethiopian highlands, north of the studied Abaya-Chamo sub-basin (Nigussie et al., 2017; Nyssen et al., 2004).

1.2.1 Check dam interventions

Check dams (Figure 3A) are a commonly implemented gully control technique, consisting of wall-like structures built transverse to the gully channel to reduce soil and water losses (Frankl et al., 2016, 2021; Guyassa et al., 2017). They can be constructed from various materials, including gabions. These wire mesh structures filled with rocks are effective but costly (Liu et al., 2019; Nyssen et al., 2004). Loose rock check dams are most widespread in the study area, created from the rocks present in and around the gully and the river (author's observation). Other materials include woven wire, locally available debris, or vegetation (Frankl et al., 2021).



Figure 3: Examples of gully interventions in Shafe catchment: (A) Loose rock check dam constructed transverse to the gully channel. (B) Example of a vegetative intervention: Banana plants established on the gully floor. Photos by author, [A: August 2025; B: September 2025] and (C) A schematic longitudinal section of check dam dimensions, including height (H), horizontal distance between dams (D), gully bottom slope (S_b), and slope gradient connecting spillway and upstream dam foot (S_n), simultaneously illustrating the stepped topography. Figure taken from Nyssen et al. (2004)

When properly implemented, check dams promote sediment deposition within the gully, contributing to gully stabilization over time (Frankl et al., 2021; Nyssen et al., 2004). Multiple check dams in a gully result in a stepped topography (Figure 3C), whereby sediment gradually infills the gully floor between dams (Wang et al., 2021).

However, Nyssen et al. (2004) found that 39% of check dams in the northern Ethiopian Highlands were destroyed within two years, primarily due to large drainage areas and steep slopes generating high runoff energy. Check dams commonly collapse during high-magnitude runoff events (Chen et al., 2024). Proper construction of check dams is thus essential for determining structural stability (Frankl et al., 2021; Nyssen et al., 2004).

Key structural design elements include an apron (a reinforced base at the bottom), a concave planform, and carefully calculated spacing between dams (Nyssen et al., 2004). When poorly constructed, check dams can even worsen erosion through bypassing or piping. However, this can be avoided by implementing a proper spillway at the top of the check dam (Nyssen et al., 2004). Figure 3C illustrates a check dam with a reverse slope (negative S_n), associated with greater structural stability (Nyssen et al., 2004). The effectiveness of check dams is further enhanced when combined with vegetation (Frankl et al., 2021; Mekuria et al., 2024).

1.2.2 Vegetative interventions

Vegetation, including plant roots, is widely cited as a key mechanism for gully stabilization (Reubens, 2010; Frankl et al., 2021). Active tree planting primarily contributes to root reinforcement of gully walls and floor (Reubens, 2010; Vanmaercke et al., 2016). Once established, vegetation can reduce flow velocity (Vanmaercke et al., 2016) and further improve soil conditions and microclimate, facilitating natural colonization of additional plant species (Frankl et al., 2021). However, while vegetation effectively traps sediment, it does not stop upslope headcut migration (Liu et al., 2019).

Grasses can additionally be planted inside gullies, though this risks reduced effectiveness through overgrazing (Nyssen et al., 2004). In the study area, this was addressed through a community-enforced fine system, where farmers collectively monitored and penalized grazing on another farmer's vegetation (informal conversation with farmers). Failure of vegetative interventions can also occur due to lack of proper water management or overall poor soil fertility (Talema et al., 2019). Additionally, the survival of vegetation is not given, as it must resist concentrated flow shear stresses during strong runoff events (Frankl et al., 2021).

A key challenge in vegetative gully stabilization therefore is the selection of appropriate species (Reubens et al., 2008; Talema et al., 2019). Successful species examples include *P. purpureum* (Elephant grass) and the indigenous tree species *S. guineense* in southwest Ethiopia. Local populations may however prefer economically valuable species like eucalypts (Talema et al., 2017, 2019). In the study area, besides grasses and trees, crops such as banana (*Musa spp.*) were often established on gully floors (Figure 3B). Talema et al. (2017) found grass species to be more effective than trees and shrubs, as they dry in the dry season, thereby covering the soil, whereas trees and shrubs do not survive and lead to poorly developed roots. However, trees fulfil other socio-economic, ecological and cultural functions, making them still relevant (Reubens et al., 2008).

1.2.3 Combination and selection of interventions

As mentioned, the combination of check dams and vegetation planting is a commonly applied and effective stabilization approach (Nyssen et al., 2004). This combination allows a large portion of the runoff behind the check dam to infiltrate, resulting in a smaller peak flow discharge (Guyassa et al., 2017; Nyssen et al., 2010). Vegetation can increase sediment trapping efficiency of check dams (Frankl et al., 2021), and can even take over their overall stabilizing role (Nyssen et al., 2004). Conversely, check dams create favourable conditions for vegetation establishment and reduce the risk of undercutting vegetation roots through sediment deposition and increased soil depth (Frankl et al., 2021). Since check dams are designed as temporary structures, the establishment of vegetation is considered the most effective complementary long-term strategy for gully stabilization (Frankl et al., 2021). Frankl et al. (2021) report a median failure rate of 24% for check dams, though vegetation can reduce this when adapted to the harsh gully environment.

Many gully control techniques have demonstrated their potential to reduce erosion and stabilize gully channels (Frankl et al., 2021; Valentin et al., 2005). However, their effectiveness in practice often remains limited, as success strongly depends on correct implementation (Nyssen et al., 2004), local environmental conditions (Frankl et al., 2021) and the degree to which communities value the intervention and how they actively manage it (Reubens, 2010). Furthermore, long-term adoption by farmers is frequently constrained by the absence of immediate benefits in terms of land or labour productivity (Bewket, 2007; Daba, 2003; Reubens, 2010; Valentin et al., 2005). Stabilizing active gullies therefore remains a major challenge (Frankl et al., 2021; Lutete Landu et al., 2023; Vanmaercke et al., 2021), raising questions about the factors that shape farmers' implementation decisions.

1.3 Factors driving gully intervention adoption

Studies consistently identify a range of interacting factors as determinants of whether and where farmers implement overall SWCM (Nigussie et al., 2017; Tesfaye et al., 2014b; Teshome et al., 2016). These factors are examined at multiple scales: from the gully itself, the spatial distance to this gully, plot-level conditions, and farmer-specific attributes, to the broader social environment.

1.3.1 Characteristics of the gully

Farmers' assessments of erosion severity has shown close alignment with the empirically determined erosion severity (Nigussie et al., 2017). In turn, perceived erosion impact is identified as a significant positive predictor of SWCM adoption (Tefaye et al., 2014b). The

physical characteristics that drive gully erosion severity (Section 1.1), such as contributing area, slope, rainfall intensity, soil type and gully width, may therefore also shape the likelihood of GI adoption, as more severe erosion may generate stronger incentives to act. Whether and how erosion severity shapes GI adoption at the individual gully level remains poorly understood, with existing evidence largely derived from broader SWCM studies rather than gully-specific research.

1.3.2 Spatial location and accessibility

Beyond the physical characteristics of the gully itself, its spatial position in the landscape may be a relevant factor for GI adoption, as it determines how easily farmers can reach it. Nigussie et al. (2017) and Teshome et al. (2016) found that plots located further from the homestead tend to receive less management and care. This may imply that gullies located on more distant plots are less likely to be treated.

Teshome et al. (2016) found that distance to the main road was not a significant predictor of SWCM adoption. For gully-specific interventions, however, distance may play a more direct role, as check dam construction requires the physical transport of materials, most notably stones, typically sourced from nearby riverbeds (author's observation). The distance to the river (materials) and road (transport) may therefore be correlated with the adoption of GIs. The exact effect of these proximity variables remains poorly understood in gully-specific context.

1.3.3 Characteristics of the adjacent plot

The previous travel time logic is specifically relevant in the study area as land fragmentation is widespread in smallholder farming systems across the Gamo district (Cholo et al., 2019). This land fragmentation can be seen as an overall surviving strategy, as the diversification of crops across agro-ecological zones decreases production risks, thus leading to less food insecurity (Cholo et al., 2019). However, as the number of plots increases, travel time between plots rises, reducing the time available for farm management and thus increasing production costs (Cholo et al., 2019). As a result, farmers with highly fragmented landholdings with large travel times between them, may have less incentive to implement GIs in their more distant plots.

Studies on general SWCM adoption consistently find that larger plots have a higher likelihood of adoption, as conservation structures on small plots compete with crops for space (Tesfaye et al., 2014b; Teshome et al., 2016). However, this logic may not directly translate to gully erosion, as a gully already occupies and destroys productive land regardless of plot size. Farmers with smaller plots additionally face proportionally greater losses from gully widening (Mekonnen et al., 2026). The expected relationship between plot size and intervention

likelihood, where bigger plot sizes is expected to lead to more general SWCM adoption, could thus even be reversed for gully-specific GI adoption.

Since gully erosion causes direct and substantial losses of productive cropland (Mekonnen et al., 2026), plots with higher agricultural value stand to lose more from an expanding gully. Beyond a loss-driven motivation, incentives may also arise from potential gains. The conversion of degraded gully land into productive use has been identified as an important benefit, therefore motivating farmer engagement (Mekuria et al., 2024). These dynamics suggest that intervention likelihood may be shaped by the perceived fertility of the plot in which the gully is located.

Whether the above plot characteristics shape GI adoption specifically, rather than general SWCM adoption, has not yet been directly investigated to our knowledge.

1.3.4 Farmer profile for gully interventions

Higher-educated farmers may be being better positioned to recognize gully erosion as a long-term threat to their land productivity (Daba, 2003). However, this awareness does not necessarily translate into action: even farmers who recognize the severity of gully erosion may still prioritize investments with more immediate returns (Daba, 2003). Additionally, higher-educated farmers tend to engage more in off-farm activities, which may reduce the time and motivation available for labour-intensive GIs (Tesfaye et al., 2014a). The net effect of education on GI adoption is therefore ambiguous and may depend on the relative strength of these competing mechanisms.

Overall, decision making in rural Ethiopian households tends to rest primarily with male household heads, though a gradual shift towards more collaborative decision-making between spouses has been observed (Fikadu et al., 2024). Male household headship has nonetheless been associated with a higher probability of implementing erosion control measures, likely due to the considerable physical labour that interventions such as check dam construction require (Tesfaye et al., 2014a). Farmer age may be another personal characteristic associated with adoption of general SWCMs, as older farmers are less likely to adopt (Teshome et al., 2016).

Livestock ownership may also shape adoption decisions. Farmers with larger livestock holdings tend to perceive soil erosion as less severe (Nigussie et al., 2017), and are less likely to adopt SWCMs, partly because grazing animals can destroy conservation structures (Tesfaye et al., 2014b), partly because larger livestock holdings generate a greater need for rangeland. Both factors could reduce the incentive to invest in land conservation measures.

Beyond personal characteristics, the material resources available to farmers may further shape GI adoption. Most farmers in the study area have limited surplus income (Mekonnen et al., 2026), making resource constraints particularly relevant. Farmers facing food insecurity may recognize gullies as a long-term threat while still lacking the incentive to act (Daba, 2003), as immediate returns tend to be prioritized over long-term gains (Daba, 2003; Reubens, 2010; Valentin et al., 2005). Access to credit may partially address this resource constraint, as it has been shown to increase the likelihood of implementing SWCMs (Tesfaye et al., 2014b). Nevertheless, this short-term logic can remain self-defeating. As discussed above, very large gullies become increasingly costly to rehabilitate (Frankl et al., 2021), therefore inaction today may lead to greater consequences tomorrow. Whether and how these farmer characteristics translate to gully-specific intervention decisions remains largely untested.

1.3.5 The social and institutional environment

Collective labour and community capacity

Labour availability could be a critical resource constraint for GI adoption, as physical interventions such as check dams require considerable collective labour input (Teshome et al., 2016). A study in the Ethiopian highlands on general SWCM found that 92% of farmers considered the technologies too labour-intensive, and 81% cited labour shortage as a main problem (Bewket, 2007). In Ethiopia, informal collective labour networks are widely present in rural contexts under different local names (e.g. *dabo*, *zafe*, *kete*), referring to farmers collaborating at varying scales to complete labour-intensive agricultural tasks (Fujimoto, 2013; Yimer, 2025). In this study, these different forms are discussed under the overarching term 'informal collective labour networks'. An example was observed during fieldwork, where groups of farmers collectively tilled each other's land in rotation (Figure 4).



Figure 4: Example of informal collective labour, likely 'zafe': groups of farmers coming together to manually till each other's land, picture taken in study area (Photo: Matthias Vanmaercke, August 2025)

This labour sharing not only distributes the workload but may also actively boost labour productivity (Mekonnen & Dorfman, 2017), enabling timely implementation during peak agricultural periods (Fujimoto, 2013). In addition, it serves as a means through which knowledge and skills are transferred from older generations of farmers to younger generations (Fujimoto, 2013).

Physical interventions such as check dams require substantial labour investment that often exceeds individual household capacity. Collective networks may reduce this barrier (Teshome et al., 2016). Farmer participation in labour sharing networks may therefore also increase the likelihood of implementing interventions (Abe et al., 2026; Teshome et al., 2016).

Land tenure status

Beyond purely physical characteristics of the gully and adjacent plot, a gully's social dimension shapes farmers' incentives to act. A key factor here is land tenure. The prevailing Ethiopian land tenure system does not guarantee farmers full ownership rights, due to government and communal property laws (Talema et al., 2017). Farmers who do not own the land are less likely to implement SWCM, as insecure land tenure reduces their incentive to invest in long-term land improvements (Daba, 2003; Talema et al., 2017; Teshome et al., 2016). Land certification has been shown to enhance investment in longer-term general SWCM practices (Adere et al., 2022), and may be relevant also for GIs adoption. Given the high degree of land fragmentation in the Gamo Zone (Cholo et al., 2019), gullies may often cross multiple plots and be shared between several farmers, potentially complicating individual intervention decisions. How shared land and gully ownership specifically affects individual intervention decisions is not yet investigated to our knowledge.

Formal institutional context

Access to technical support and information about suitable land management technologies may increase the likelihood of maintaining general SWCM structures (Tesfaye et al., 2014a). Information and knowledge can spread through both formal and informal channels (Abdulai et al., 2021; Genius et al., 2014). Agricultural extension agents, referred to as Development Agents in Ethiopia, are government-employed workers stationed in local administrative units who transfer agricultural knowledge and techniques directly to farmers. Their presence may be positively associated with farmers' perception of soil erosion severity (Nigussie et al., 2017), and general SWCM adoption (Abdulai et al., 2021). Even simplified information provision through brochures can increase the voluntary adoption of techniques, with effects being strongest in remote areas where information is generally limited (Abe et al., 2026).

However, formal knowledge provision alone may not always be sufficient to drive adoption.

Farmers may remain sceptical about the feasibility of interventions, particularly when they have no direct experience with successful cases (Ayele et al., 2015). This is demonstrated by Ayele et al. (2015) in a participatory gully rehabilitation project supported by researchers and local institutions in the Ethiopian Highlands. Initially, farmers were hesitant, perceiving the gully rehabilitation as impossible due to physical, economic, and religious factors. However, after the rehabilitation was carried out, the mindset of the local population changed: on their own initiative, farmers rehabilitated five new gullies in the following year (Ayele et al., 2015). Ayele et al. (2015) argue that this perceived feasibility, shaped by community experience, can be as decisive as physical constraints in driving adoption.

This illustrates how formal institutional support may initiate the process, while direct observation of successful cases (an informal mechanism) can overcome resting scepticism. Observing nearby successful GIs may lower the risk perceived by hesitant farmers and stimulate their own adoption

Informal neighbourhood context

The spread of adoption does not necessarily need to be indicated by formal means. Studies across diverse domains, including agriculture, show that the probability of adopting an innovation increases as more individuals in the immediate social environment of have previously adopted this innovation (Abdulai et al., 2021; Valente, 2005; Wu et al., 2018). Some farmers therefore act as early adopters, whose visible success lowers the perceived risk for hesitant neighbours. This process, described as network exposure, can trigger a chain of subsequent adoptions across the broader community (Valente, 1996).

Network exposure effect may have less influence on adoption decisions at the beginning of the process, when few neighbours have adopted and the advantages of waiting are still apparent, and at the end, when the vast majority has already adopted (Valente, 1996). This may therefore give rise to a diffusion effect in which distinct clusters of adoption can emerge, with adoption spreading faster within clusters than between them (Valente, 2005). Therefore, the timing of adoption does not only depend on whether a neighbour adopts, but specifically on when a neighbour adopts (Abdulai et al., 2021; Wu et al., 2018), and on how large the group of prior adopters is (Genius et al., 2014). Moreover, this tends to occur faster between individuals who share similar social characteristics, such as age, education and farming activities, thereby creating a diffusion trend in which geographic proximity and social network ties reinforce each other (Abdulai et al., 2021; Genius et al., 2014).

For the spread of conservation agriculture techniques specifically, this social diffusion effect was examined by Abdulai et al. (2021), who statistically confirmed peer-driven diffusion using

a discrete-time hazard model on survey data from smallholder farmers in Zambia. The role of geographic distance in the spread of agricultural practices was investigated by Genius et al. (2014), who used another type of hazard model on recall survey data from olive farmers in Crete. They found that geographically closer neighbours exert stronger influence on each other, and argued that this informal diffusion and formal channels may amplify each other (Genius et al., 2014). To our knowledge, whether formal and informal social and spatial diffusion dynamics also apply to GIs adoption remains unstudied.

1.3.6 Species selection and economic trade-offs

Species selection for gully stabilization is strongly shaped by local economic preferences rather than expert recommendations alone (Reubens, 2010; Talema et al., 2017). This reflects a broader tension inherent to gully intervention decisions: farmers operating under conditions of food insecurity and limited surplus income must weigh the immediate economic returns of any intervention against its long-term conservation value (Daba, 2003; Valentin et al., 2005). At the same time, gully erosion directly threatens plot productivity (Frankl et al., 2021; Mekonnen et al., 2026), creating incentive to act, particularly when the chosen intervention also generates income.

In this context, banana (*Musa* spp.) is a relevant example (Figure 3B). It is widely grown as a cash crop and a source of household food security by smallholder farmers in Ethiopia. The Gamo zone alone, in which the Shafe catchment is located, accounts for over 80% of total bananas marketed in the country (Bekeko et al., 2025). Banana plants have a dense root system that can form a compact mat in the upper soil layer (Siddiq et al., 2020), which may contribute to gully stabilization in similar manners as other vegetation discussed above. However, banana productivity in the zone has been declining due to land degradation processes (Bekeko et al., 2025), making the dual function of banana as both economic crop and potential stabilization measure particularly relevant.

Profitability has been identified as the primary reason for adoption of SWCM in a study of Addis et al. (2020). For implementing more successful and sustainable GIs in the future, it is therefore vital to understand what is relevant for farmers and why they prioritize this. This bottom-up perspective forms the central motivation of this study.

1.4 Research gap, relevance, objectives and questions

Despite growing attention to adoption of gully interventions in sub-Saharan Africa, several gaps remain. Most studies examine either physical or socio-economic drivers in isolation, and few integrate both in a single analytical framework (e.g. Nigussie et al., 2017; Teshome et al.,

2016). Studies focusing on gully-level GI adoption, as opposed to broader soil conservation, remain scarce. This leaves many factors empirically untested regarding their impact on implementation of GIs specifically. Furthermore, while spatial diffusion of agricultural innovations has been documented (e.g. Abdulai et al., 2021), it has, to our knowledge, never been applied to gully erosion control specifically.

This study addresses these gaps by examining GI adoption at the individual gully level in the Shafe catchment, southern Ethiopia. In doing so, the study adopts a bottom-up perspective that starts from observed farmer behaviour to understand which gullies communities choose to rehabilitate, and which they do not. Linking physical, socio-economic, and spatial diffusion factors in an integrated framework, the findings aim to contribute to the scientific literature on GI adoption.

In contexts where gully erosion directly threatens the livelihoods of households already facing severe food insecurity (Mekonnen et al., 2026), understanding what drives GI adoption is not merely an academic question. In the Shafe catchment specifically, the AMU-IUC project has been active in organizing voluntary demonstration workshops on gully rehabilitation, providing farmers with technical guidance on check dam construction and vegetation planting. Emphasis is placed on correct construction practices, in line with guidelines for structural stability (Nyssen et al., 2004). By identifying factors from a bottom-up perspective that impact farmers' decision making, the study seeks to inform these and other top-down development strategies for designing more targeted gully rehabilitation programs in Ethiopia and similar contexts. This makes this study societally highly relevant. It therefore addresses four key objectives:

1. To document gully interventions implemented in gullies and map their spatial distribution.
2. To identify and assess the physical and socio-economic factors influencing the spatial distribution (where), and decision-making (by whom) of GI adoption in gullies.
3. To develop predictive models, based on these insights, to identify which gullies are most likely to be prioritized for treatment.
4. To assess the dynamics of GI adoption over time and investigate whether their spread occurs via a diffusion process.

In line with these objectives, this study seeks to answer the following main research question:

“How do farmers respond to gully erosion in the Shafe catchment, and what drives variability in gully intervention adoption?”

More specifically, this study seeks to answer the following research sub-questions:

1. What GIs have been implemented so far by farmers to reverse gully-induced problems, and how are these interventions spatially distributed?
2. Which socio-economic, physical and perceptual factors explain why some gullies are treated, while others are left untouched over time?
3. To what extent can predictive models identify which gullies are most likely to be prioritized for intervention?
4. To what extent does GI adoption across the Shafe catchment show evidence of a spatial diffusion process?

Based on the literature review above, the hypotheses of this research corresponding to these research questions are:

H1: More severe cases of gully erosion (i.e. larger area, steeper slopes) are more likely to be treated with GIs.

H2: Gullies that are better accessible and closer to resources (i.e. closer to roads, rivers and homestead settlements) are more likely to be treated with GIs.

H3: Gullies located in more (perceived) fertile and securely owned land are more likely to be treated with GIs.

H4: Farmers with sufficient economic surplus, labour capacity and material support, but a greater dependence on agriculture as primary livelihood are more likely to implement GIs

H5: Farmers are more likely to implement GIs when geographically neighbouring gullies have already been treated, suggesting spatial diffusion through formal or informal peer influence.

CHAPTER 2

METHODS

This chapter outlines the methodology used to address the research questions of this study. First, the study area is described, followed by the data collection procedures. Subsequently, the variables derived from these datasets and the analytical frameworks are presented. Figure 5 provides a schematic overview of the methodological steps taken in this study, from data collection and variable selection to analysis and modelling, colour-coded by research question.

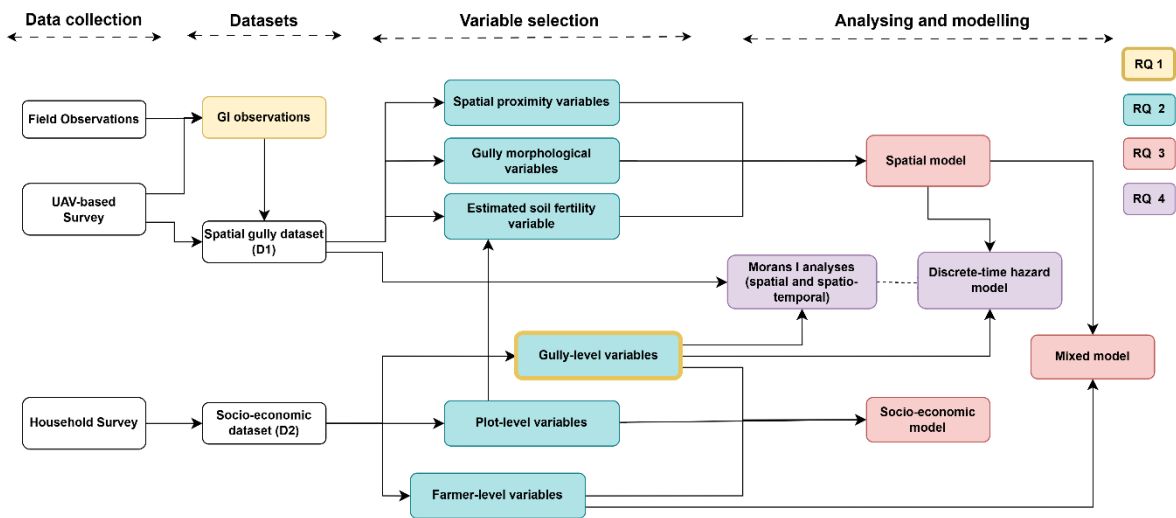


Figure 5: Schematic overview of the study design, illustrating data collection, datasets, variable selection, and analysis. Colour coding indicates the corresponding research question: RQ1 (yellow), RQ2 (blue), RQ3 (red), and RQ4 (purple). Dual-coloured elements contribute to multiple research questions.

2.1 Study area

2.1.1 Positioning of the study area

The Abaya-Chamo sub-basin is located in the southern Rift Valley of Ethiopia (Figure 6A), extending between 5°51.5'N to 8°8'N latitude and 37°16.3'E to 38°39.3'E longitude (Gebeyehu et al., 2019). This study focuses on the Shafe catchment specifically (Figure 6C), situated on the western side of Lake Abaya, about 451 km south from the capital, Addis Ababa (Abeje et al., 2025). Altitudes range from 1,171 to 3,051 m above sea level (Mekonnen et al., 2026), covering an area of approximately 205 km² (Belayneh et al., 2022). The catchment contains about 3,640 gullies, representing nearly 50% of the total gullies identified in the broader sub-basin (Belayneh et al., 2022). The gully length density in the Shafe area reaches 3.5 km/km². 63% of these gullies remain active (Belayneh et al.,

2022), highlighting the ongoing land degradation (Mekonnen et al., 2026).

The Shafe catchment includes 13 rural kebeles (Gamo Zone Agricultural Department, 2020), which are the smallest administrative units in Ethiopia, containing several villages (Abeje et al., 2025). This research focuses on two of these kebeles: Layo Terga and Morode, which were chosen because of the extensive amount of gullies in these specific areas and synergies with earlier research (i.e. Belayneh et al., 2022; Mekonnen et al., 2026).

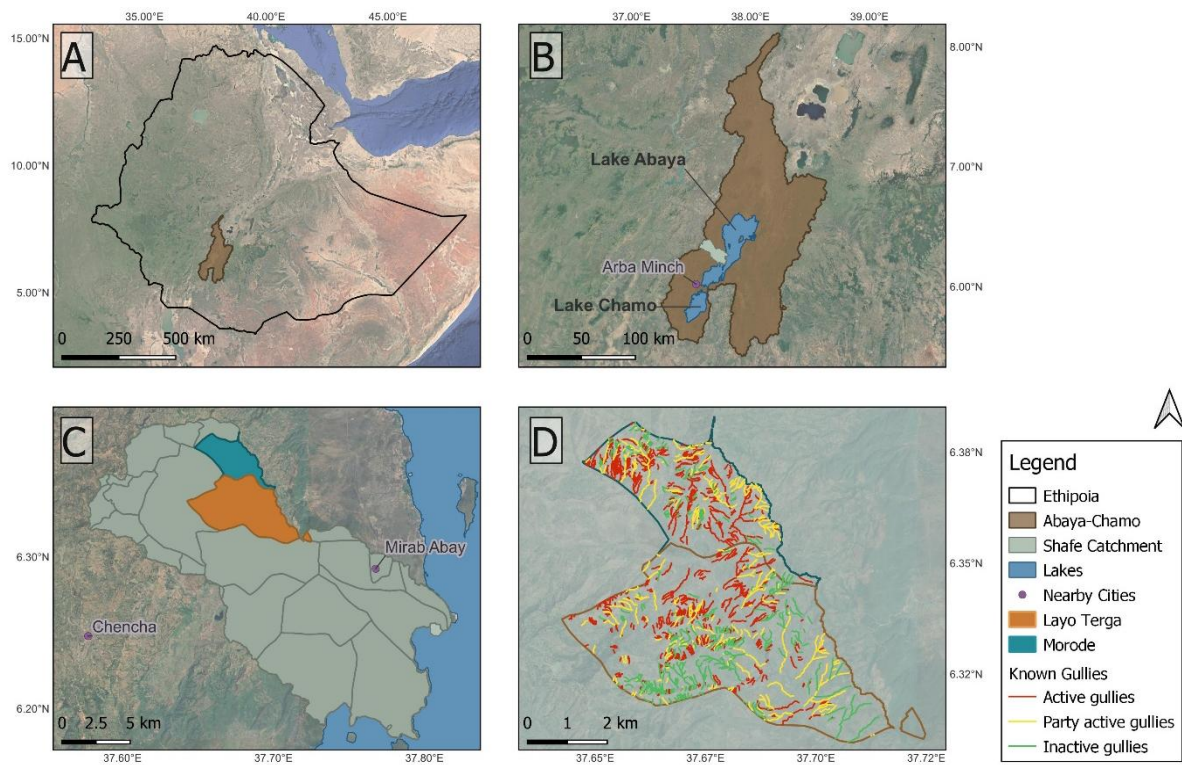


Figure 6: Location of the study area (A) the Abaya-Chamo sub-basin in Ethiopia, (B) the Shafe catchment Abaya-Chamo sub-basin, (C) the kebeles (Layo Terga and Morode) and (D) an overview of the mapped gullies and activity status in the two kebeles. Administrative boundaries: Ethiopian GeoPortal (ESRI); Gully data derived from Belayneh et al. (2022); Background imagery: © Esri World Imagery.

Previous research highlights the severity of erosion in the Shafe catchment. Abeje et al. (2025) estimate total soil loss at approximately 57,600 Mt, placing the catchment among the most severe eroded areas in the region. While numerous GIs have already been implemented in the study area (Mekonnen et al., 2026), many locations still lack GIs. This provides an ideal context to examine the implementation and decision-making processes regarding GIs, as the presence and absence of these interventions within a relatively narrow spatial area allows for a direct comparison.

2.1.2 Physical characteristics

Geology and soil

The Abaya-Chamo sub-basin is part of the Main Ethiopian Rift (Belayneh et al., 2022) where the geology is dominated by intrusive and extrusive igneous rocks (e.g. basaltic and trachytic lava flows) while Holocene fluvial deposits occur predominantly on the valley floor (Belayneh et al., 2022). These geological processes have shaped the study area into a rugged and mountainous landscape (Shano et al., 2022). The dominant soil types of the Shafe catchment are Chromic Vertisols, Eutric Fluvisols, Dystric Fluvisols, Dystric Nitisols and Orthic Acrisols (Abeje et al., 2025).

Climate

The Abaya-Chamo sub-basin is characterized by a tropical savanna climate with a bimodal rainfall pattern, where two rainy seasons typically occur from the end of March to mid-June and from mid-September to late November (Abeje et al., 2025; Belayneh et al., 2022; Gebeyehu et al., 2019; Mada & Nannawo, 2023). Temperatures range from approximately 15 to 32°C, with a mean annual temperature of around 23°C (Mada & Nannawo, 2023). The Shafe catchment specifically receives an average annual rainfall of approximately 1,014 mm (Abeje et al., 2025), and is predominantly characterized by semi-humid (71%) and cold humid (25%) climatic zones (Mada & Nannawo, 2023). Monthly rainfall and temperature patterns are illustrated in Figure 7, based on data from Arba Minch, Mirab Abaya, and Chenchha stations (1995–2021).

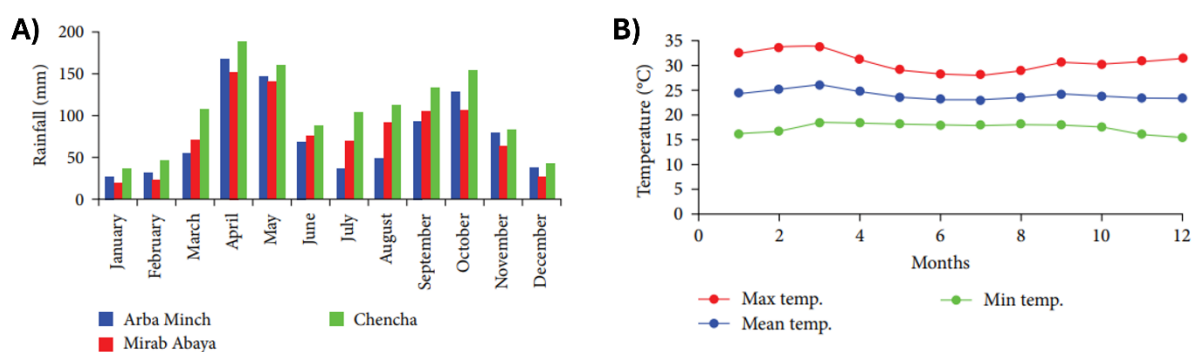


Figure 7: (A) Mean monthly rainfall (mm) for three stations in and around the Shafe catchment (1995–2021) and (B) maximum, minimum, and average monthly temperature (°C) at Arba Minch station (1995–2021). Source: Mada & Nannawo (2023)

Land use and land cover

The main land use and land cover types in the Shafe catchment as of 2021 are agricultural land (35%), shrubland (29%), grassland (22%), and forest (14%) (Mada & Nannawo, 2023). Agricultural land has expanded significantly, from 21% in 1998 to 35% in 2021, while forest cover declined from 22% to 14% over the same period, increasing surface runoff and erosion risk (Mada & Nannawo, 2023). Combined with the steep topography, where nearly 70% of the catchment has slopes exceeding 30%, the land cover, land use, soil and climatic characteristics are key drivers of runoff concentration and gully formation in the area (Abeje et al., 2025; Mada & Nannawo, 2023).

2.1.3 Smallholder farming social context

Agriculture is the primary livelihood of people living in the Gamo Zone, with the most frequently cultivated crops being ‘false banana’ (*enset*), barley, maize, sweet potato, and teff (Amsalu, 2024). As in many other regions in Ethiopia, subsistence farming dominates, with approximately 85% of the population depending on agriculture as their primary source of income (Alemu et al., 2002). Of these agricultural practices, banana cultivation is well established in the Shafe catchment, and the Gamo zone accounts for over 80% of the total bananas marketed in Ethiopia (Bekeko et al., 2025). Earlier work in the study area indicates that bananas are increasingly observed inside gullies (Mekonnen et al., 2026).

As in many other regions in Ethiopia, agricultural production is dominated by rain-fed agriculture (Feyso & Mensa, 2021) that is highly sensitive to climate change due to its strong dependence on rainfall patterns, and its sensitivity for temperature variability and extreme weather events (Tofu et al., 2022). This leads to a very high food insecurity number, even in years with relatively favourable rainfall conditions (Cholo et al., 2019). In the Gamo zone of southern Ethiopia, food insecurity is particularly severe, with between 93% and 95% of households experiencing some form of food insecurity (Cholo et al., 2019).

Lastly, land fragmentation is very common in the Shafe catchment. Farmers typically manage multiple dispersed plots, on average 3.4 fields per household, ranging from 1 to 13 (Mekonnen et al., 2026). Land preparation is primarily carried out through manual tillage using hand hoes (Mekonnen et al., 2026). To tackle part of the workload problem, informal collective labour networks (see Section 1.3.5) are commonly practiced (Fujimoto, 2013; Yimer, 2025).

2.2 Data Collection

Data were collected during a field campaign from 11 August to 20 September 2025 in the Shafe catchment, comprising 21 fieldwork days across the Layo Terga and Morode kebeles. The campaign consisted of two sequential phases: a first phase of Unmanned Aerial Vehicle (UAV)-based surveys and field observations to map gullies and document implemented GIs, followed by a household survey phase to collect socio-economic data.

2.2.1 UAV-based survey

To obtain an overview of the different GIs present in the study area, UAV-based surveys were conducted. As each battery flight covers a limited area, the study area was divided into 22 designated case areas, 13 in Layo Terga and 9 in Morode, each corresponding to a single flight (Figure 8B). In total, 14 days of UAV-based surveys were carried out between August 13 and September 6, 2025.

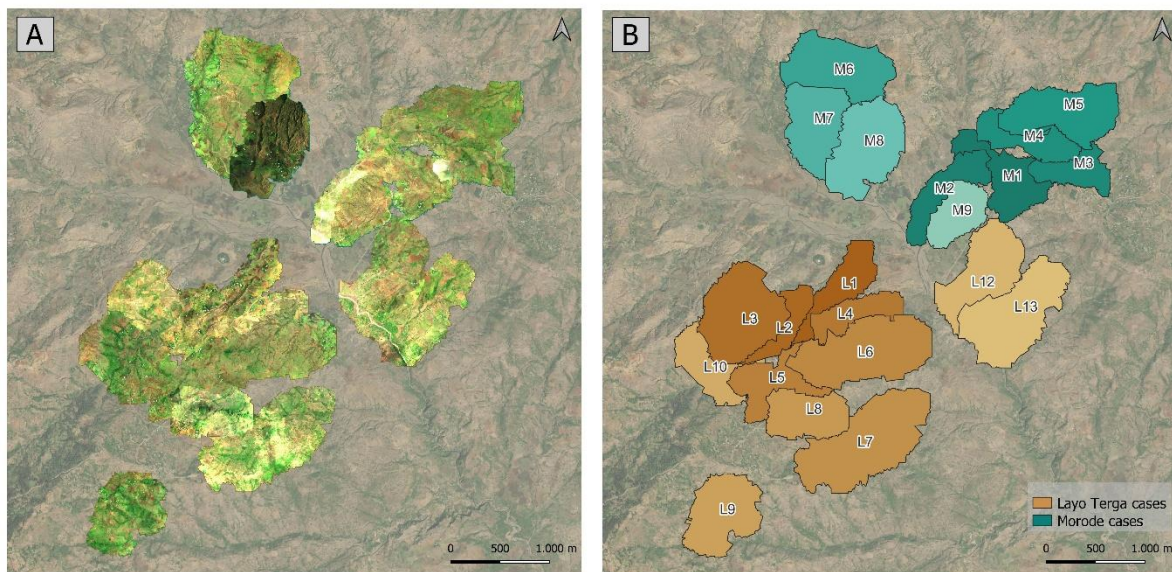


Figure 8: (A) Mosaic of all processed orthophotos covering the study area. (B) Spatial distribution of the 22 designated case areas across the two kebeles: 13 in Layo Terga (L, orange) and 9 in Morode (M, blue). Background imagery: © Esri World Imagery.

A DJI Matrice 300 RTK equipped with a MicaSense RedEdge multispectral camera was used. Flights were executed by co-supervisor Y. Mekonnen using DJI Pilot software at an altitude of approximately 80 m above the highest point of the surveyed area, with a forward overlap of 75%, a side overlap of 65%, and a flight speed of 10 m/s.

Image quality was assessed in Agisoft Metashape (v2.1.2) using the "Estimate image quality" tool, which evaluates sharpness, exposure, and other factors. Images with a quality score below 0.80 were excluded from further processing. The remaining imagery was processed by

co-supervisor Yibeltal Mekonnen as part of his ongoing PhD research, following the standard photogrammetric workflow, including spectral calibration, image alignment, generation of dense point clouds, and creation of Digital Elevation Models (DEMs) and mosaics of processed orthophotos (orthomosaics) at spatial resolutions ranging from 5 to 20 cm. Figure 8A shows a mosaic of all processed orthophotos.

2.2.2 Mapping of gullies

In this study, GI implementation is determined at the gully level. A clear delineation of what exactly constitutes a gully is therefore necessary. A feature was considered an individual gully if it (1) displayed a clear headcut, (2) had a minimum thalweg length of 30 m from headcut to outlet or confluence with another part of the drainage network, and (3) did not function as a permanent stream channel. The length criterion was used to distinguish individual gullies from short erosional features and to separate branches within larger gully systems, consistent with gully mapping approaches in other contexts (Mawe et al., 2025). In some cases, branches shorter than 30 m were nonetheless included when they were clearly visually distinct and functionally separate, for instance when they would be perceived as a clearly separate unit from a farmer's perspective. In total, 5.1% of mapped gullies have a thalweg length below 30 m, of which the vast majority (4.2% of all mapped gullies) fall between 20 and 30 m. Rills were not included in the dataset. Lastly, erosional features showing continuous baseflow and clear characteristics of an established stream channel (see Figure 2) were excluded, as these are considered part of the permanent drainage network rather than active gully systems.

Building on the earlier gully inventory of Belayneh et al. (2022), all gullies within the UAV-surveyed area were (re)mapped based on the UAV-derived orthophotos and DEMs. Additionally, gullies that were missing from the earlier mapping of Belayneh et al. (2022) were included.

Gullies were manually delineated as polygons in QGIS (version 3.28.4, Firenze), based on the UAV-derived orthophotos (Figure 9A). To improve the visibility of gully boundaries, hillshade layers derived from the UAV-derived DEMs were overlaid on the orthophotos (Figure 9B). The spatial extent of the mapped gullies is therefore limited to the areas covered by the UAV-based survey, though the flight planning was designed to ensure that all major gullies in the study area were fully captured. This resulted in a total of 751 mapped gullies across the two kebeles.

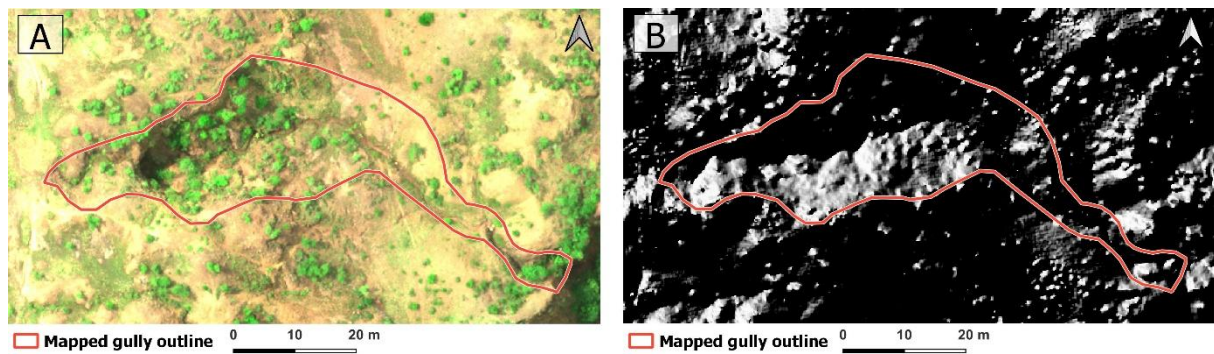


Figure 9: Example of a mapped gully outline (Layo Terga, Case 4) on (A) the UAV-surveyed orthophoto and (B) the UAV-surveyed orthophoto overlaid with the DEM-derived hillshade. The red outline indicates the manually delineated gully polygon.

2.2.3 Field observations

Field observations were carried out within each orthophoto patch immediately after or during the UAV-based survey flights. Within each patch, the team walked through the area together with local development agents (Section 1.3.5) systematically searching for gullies containing GIs (Figure 10). While the aim was to cover the full extent of each patch, complete coverage of every gully could not always be guaranteed (e.g. due to accessibility constraints).

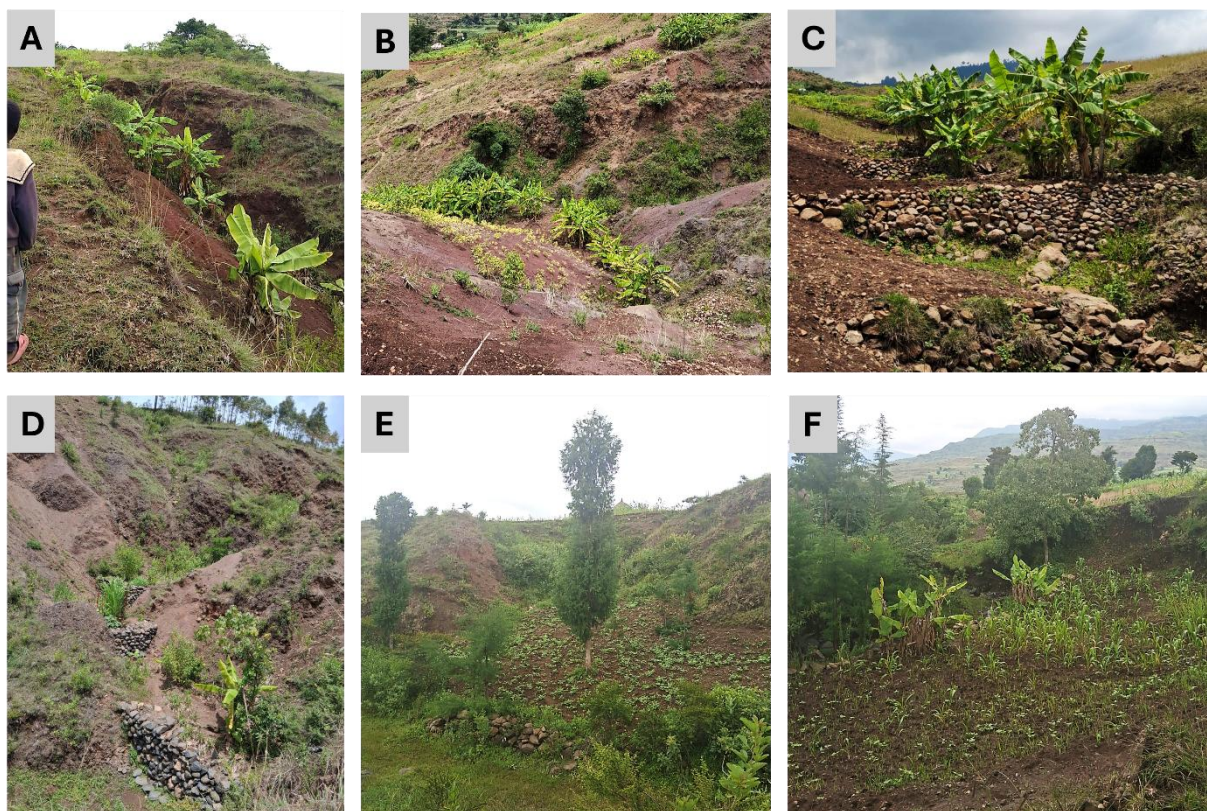


Figure 10: Examples of field GI observations: (A) banana i (Case Morode 2), (B) banana and crop (Sorghum) in gully (Case Layo Terga 3); (C) Banana and check dam (Case Layo Terga 1); (D) Sequence of check dam with banana and grass additions (Case Layo Terga 1); (E) Combination of tree, crop and check dam (Case Layo Terga 12) and (F) a combination of banana, crop and grass (Case Layo Terga 12).

During the field observations, the GPS location of each observed intervention group was recorded. An intervention group is defined as a combination of one or more GI implemented by a single farmer within a specific section of a gully, typically within or bordering their plot. For example, a check dam combined with banana planting would be recorded as one intervention. However, if two farmers decided to implement check dams and/or bananas along the same gully, each within the section within or neighbouring their plot of land, this would be recorded as two groups. Figure 10B-F show examples of a combination of interventions, resulting in one intervention group. Each intervention group was assigned a unique intervention ID, and the types of the individual interventions within the group were documented.

Each observed GI group was thereby recorded per gully and per plot and, where possible, linked to the corresponding farmer, identified either by the development agents or by nearby farmers. In total, 128 GI groups were identified through field observations, predominantly consisting of banana plantations and check dams.

2.2.4 Identification based on UAV-based imagery

Following the field observations, the UAV-derived orthophotos were used in two ways. First, the GPS points recorded during field observations were used to locate each observed intervention on the orthophotos, allowing their spatial extent to be mapped more precisely through digitization. For banana interventions specifically, the actual boundaries were digitized as polygons to calculate the area occupied inside the gully, from which a centroid point was derived. For all other GIs, including check dams, a single point location per individual intervention was recorded. Within an intervention group, each individual intervention type was therefore represented by its own point. For example, a group containing a banana plantation, a check dam, and a tree plantation would result in three separate point locations.

Second, all mapped gullies were systematically checked on the orthophotos for additional GIs not identified during field visits, using the field-observed interventions as a visual reference to recognize similar features elsewhere in the imagery. In total, 56 additional grouped interventions were identified, bringing the total number of observed grouped interventions to 184.

The MicaSense RedEdge multispectral camera provides imagery in five spectral bands: Blue, Green, Red, RedEdge, and Near-Infrared (NIR). Intervention types were primarily identified using true-colour (Red-Green-Blue) composites, as most features were visually distinguishable based on their natural appearance. Where contrast was insufficient, multiple false-colour composites were additionally explored. Banana plantations were identified by their distinctive

canopy in true-colour composites, with false-colour composites further enhancing their visibility through strong RedEdge or NIR reflectance (Figure 11 A-B). Check dams lack a distinct spectral signal and were therefore primarily identified in true-colour composites, with false-colour composites occasionally used to enhance contrast between the dam structure and surrounding vegetation (Figure 11 C-D). Other interventions, such as grasses, could not be reliably identified from remote sensing alone and were documented through field observations.

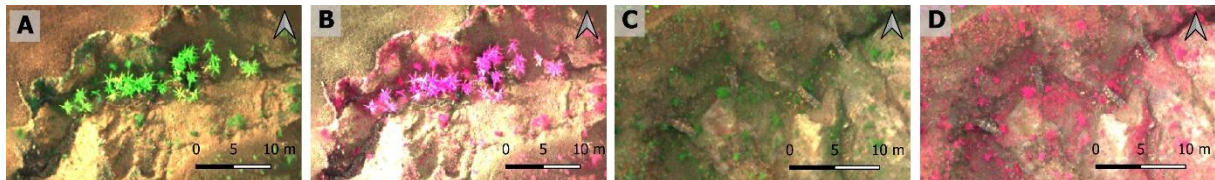


Figure 11: Visual identification of gully interventions in UAV orthophotos. (A) True-colour composite (Red-Green-Blue) and (B) False-colour composite (RedEdge-Red-Green) showing banana plantations (C) True-colour composite (Red-Green-Blue) and (D) False-colour composite (RedEdge-Red-Green) showing check dam sequence and enhancement of contrast on false-colour images.

2.2.5 Household survey

Ethical approval for the study was obtained from the KU Leuven Social and Societal Ethics Committee (SMEC) (PRET approval number: G-2025-9211, Appendix F). A household survey questionnaire was co-designed prior to the field campaign in collaboration with co-supervisor Yibeltal Mekonnen and supervisor Matthias Vanmaercke, building on earlier knowledge of the study area. The questionnaire was refined in two stages: first, following the first phase of fieldwork (UAV-based survey and field observations) based on new information gained in the field (i.e. on plot fragmentation patterns and gullies crossing multiple plots). Second, following informal interviews conducted during gully rehabilitation demonstration on 29 August 2025 (AMU-IUC project, Layo Terga), which revealed the importance of labour and material support as explicit response options. The final questionnaire was administered digitally using the KoboCollect application (KoboToolbox, 2025), provided in Appendix G.

The household survey was conducted in the local language(s) from 12 September to 19 September 2025 by five trained enumerators from Arba Minch University. A total of 178 households were randomly selected from Layo Terga and Morode, representing an acceptable sample size following Cochran (1977). Informed consent was obtained from all participants and the confidentiality of their responses was assured.

The survey was structured across three hierarchical levels: farmer ($n = 178$), plot ($n = 965$), and gully ($n = 988$). At the gully level, farmers with at least one intervention were asked additional questions per intervention type, comprising farming (e.g. bananas, sorghum, $n =$

298), physical (e.g. types of check dams, $n = 380$), and grass ($n = 174$) interventions, as illustrated in Figure 12.

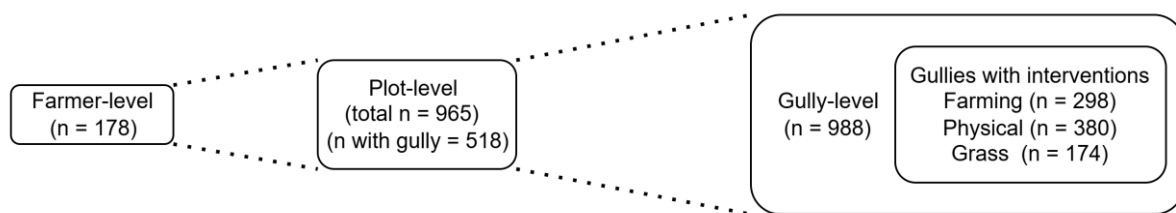


Figure 12: Schematic household survey structure

At the farmer level, demographic characteristics were first collected for the 178 interviewed farmers, including age, gender, education level, household size, and years of farming experience. Economic status was also recorded, covering annual household income and expenses, income strategies (e.g. farming only or mixed), house type, livestock ownership, and number of plots managed.

For each plot owned by a farmer, plot-specific questions were asked, covering plot size, tenure status, years farmed, crops grown, total yield last year, self-reported productivity, and travel time from the homestead. This resulted in information on 965 plots. Farmers were additionally asked whether at least one gully was present in or bordering the plot. Evidently, not all reported plots contained gullies, while some plots contained multiple.

988 gullies were reported, distributed across 518 unique plots. At gully level, questions covered the number of years since the gully was first observed, gully activity, gully ownership (sole ownership or 'shared' in the case the gully ran through or bordered multiple plots owned by different farmers), perceived impact score, and main impacts observed. Farmers were additionally asked whether GIs were present inside the gully and upslope of the gully.

Where GIs were present inside the gully, the survey continued at the level of the gully to collect more data on the interventions. A distinction was made between farming (crops and trees), physical interventions and grass planting inside the gully, and upslope GIs. The latter group was not further analysed in this study but remains relevant to the broader scope of the project. For each GI type inside the gully, multiple-choice questions were asked about implementation details.

The survey additionally included two supplementary components. Farmers were asked about their future intentions regarding GI implementation and their primary reasons thereof. Farmers

who had previously attended a gully rehabilitation workshop were asked whether participation had changed their understanding of GIs.

2.2.6 Data integration

This study draws on four distinct datasets, each derived from one or more data collection approaches described above.

The so-called ‘spatial dataset’ (*Dataset 1*), consists of 751 mapped gullies, each classified as treated ($n = 135$) or untreated ($n = 616$) based on the presence or absence of at least one GI (schematic overview in Figure 13). GIs were identified through field observations ($n = 128$ grouped interventions, Section 2.2.3.) and UAV-based image interpretation ($n = 56$ grouped interventions, Section 2.2.4). A single gully can contain multiple grouped interventions from different farmers, which is why the number of grouped interventions (184) exceeds the number of treated gullies (135).

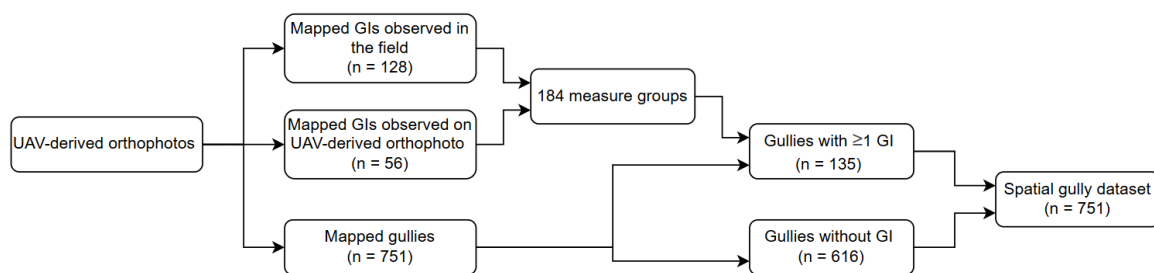


Figure 13: Schematic overview of the construction of the spatial dataset (*Dataset 1*), based on field observations and UAV-based image interpretation. Numbers indicate grouped GIs and mapped gullies.

The ‘socio-economic dataset’ (*Dataset 2*) was derived from the household survey and is as such independent of Dataset 1. It covers 988 gullies reported by 178 farmers at farmer, plot, and gully level, as described in Section 2.2.5.

Next, these two datasets were linked as much as possible to enable the analyses addressing RQ2, RQ3 and RQ4. This linking was inherently complex for several reasons. A single gully in the spatial dataset may correspond to multiple observations in the socio-economic dataset, as multiple farmers can border and report on the same gully. Conversely, a single farmer may report multiple gullies. As the spatial dataset lacks socio-economic information and the socio-economic dataset lacks specific spatial gully characteristics, unambiguous linking was only possible for a subset of gullies.

The actual linking process was further constrained by two practical factors. First, farmers were mostly interviewed away from their fields, making it impossible to directly derive the location of each reported field and, consequently, each gully. Second, a large fraction of gullies mentioned by farmers falls outside the UAV-surveyed area.

For treated gullies, linking proceeded hierarchically across three levels (Figure 14). Of the 184 observed grouped interventions, 137 could be linked to a farmer in the socio-economic dataset (82 unique farmers), 105 to a specific plot (75 unique plots), and 91 to a specific gully (71 unique gullies). For untreated gullies, additional field visits yielded 105 untreated spatial gullies linked at farmer level. Only unambiguous matches were retained throughout.

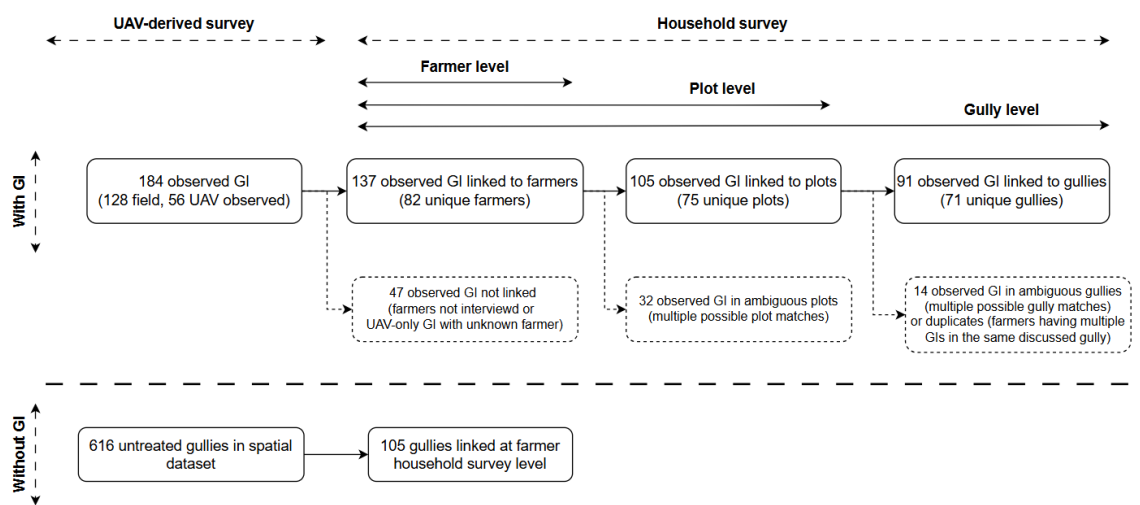


Figure 14: Linkage between the UAV-derived observations and household survey data for treated gullies (top) and untreated gullies (bottom), showing the number of matched observations at each level. The level of detail and information available increases from left to right.

This linking procedure resulted in two additional datasets that were used in further analyses. The farmer-level linked dataset (Dataset 3) contains 242 rows (137 treated gullies, 105 untreated gullies), covering 193 unique gullies across 102 farmers for which both spatial and socio-economic data are available. Each unique farmer-gully pair forms one observation, as the socio-economic characteristics of each individual farmer are independently relevant for explaining their adoption decision. A gully shared between multiple farmers may therefore appear more than once, explaining why Dataset 3 contains 242 rows despite covering only 193 unique gullies.

The gully-level linked dataset (Dataset 4) contains 71 unique treated gullies for which both spatial information and gully-level survey responses were available. Here, the unique gully is the unit of analysis, as this dataset is used for the spatio-temporal diffusion analysis where each gully has one spatial location. Socio-economic information for untreated gullies is not

available at this level. Because this dataset is used for the diffusion analysis, the unlinked gullies from the spatial dataset were added, leading to a dataset of 71 linked gullies with GI, 64 unlinked gullies with GI and 616 gullies without GI in dataset 4.

An overview of the four datasets is provided in Figure 15, hereafter referred to as Dataset 1 (D1), Dataset 2 (D2), Dataset 3 (D3) and Dataset 4 (D4).

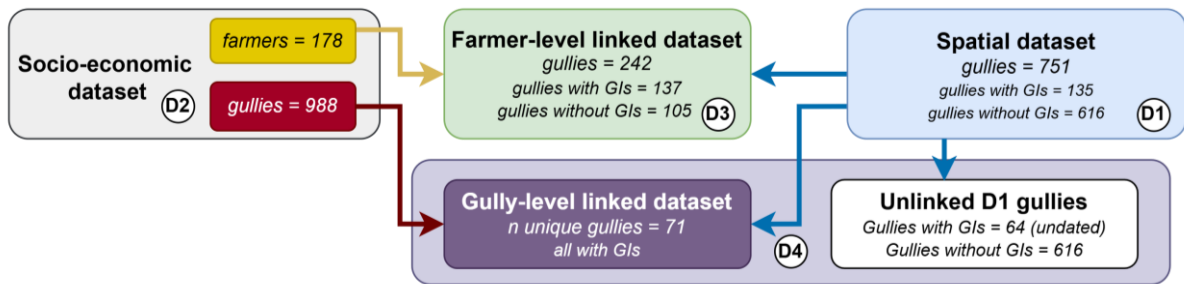


Figure 15: Overview of the four datasets used throughout this study. Dataset 1 (D1, blue): spatial dataset of 751 mapped gullies; Dataset 2 (D2, grey): socio-economic dataset of 988 gullies reported by 178 farmers; Dataset 3 (D3, green): farmer-level linked dataset of 242 gully-rows; Dataset 4 (D4, purple): gully-level linked dataset of 71 unique gullies and additional unlinked gullies from the spatial dataset.

2.3 Assessment of variables influencing gully intervention adoption

2.3.1 Considered Variables

Physical variables

For each gully in D1, a series of physical variables were extracted/calculated. These can be divided into three main categories: (i) gully morphological characteristics, (ii) spatial proximity variables, and (iii) estimated soil fertility variables.

These variables (Table 1) were selected based on their documented role in gully dynamics and/or GI adoption as identified in the literature (Section 1.3). Morphological variables such as gully area, length, width, slope, and elevation difference characterise the overall scale and severity of the gully, whereby steeper slopes in particular have been associated with higher erosion rates and structural instability (Vanmaercke et al., 2016, 2021). Spatial proximity variables were included since the accessibility of a gully may determine both the frequency of farmer visits and the feasibility of transporting construction materials (Nigussie et al., 2017; Teshome et al., 2016). Lastly, soil fertility proxies were included since plots of higher

agricultural value may stand to lose more from gully expansion, and may additionally offer greater potential for productive use of the gully floor (Mekonnen et al., 2026).

Table 1: Overview of physical variables derived for each gully in D1

Variable	Unit	Description	Source
Gully morphological variables			
Total area	m ²	Total area of digitised gully polygon	UAV-derived orthophoto/DEM
Total length	m	Thalweg length of gully from headcut to outlet	UAV-derived orthophoto/DEM
Mean width	m	Mean width of gully : Area / Thalweg length	Derived
Elevation	m a.s.l	Absolute elevation at gully centroid	UAV-derived DEM
Elev. diff.	m	Elevation drop along thalweg	UAV-derived DEM
Mean slope	°	Mean terrain slope at gully centroid	UAV-derived DEM
Estimated soil fertility variables			
Weighted N 0-30cm	cg/kg	Depth-weighted average Nitrogen-content (N-content) of topsoil (0–30 cm) at gully centroid	ISRIC (2026)
Spatial proximity variables			
Dist. main road	m	Euclidean distance from gully centroid to main road	Google Earth (2023)
Dist. sec. road	m	Euclidean distance from gully centroid to secondary road	Google Earth (2023)
Dist. River	m	Euclidean distance from gully centroid to river	Google Earth (2023)
Dist. nearest road	m	Min(main road distance, secondary road distance)	Derived
Dist. nearest house	m	Euclidean distance from gully centroid to nearest building	Google Earth (2023)
KDE settlement pressure (50, 100, 150, 200, 300 or 500)	-	Kernel density estimation of settlements at radii 50/100/150/200/300/500 m, at gully centroid	Google Earth (2023)

Gully morphological characteristics were derived from the digitised gully polygons and UAV-derived DEMs using QGIS (Sections 2.2.1 and 2.2.2). Thalweg length (referred to as total

length) was manually mapped based on visual interpretation (Section 2.2.2). All remaining morphological variables were derived directly from the polygon geometry or DEM.

(Estimated) soil fertility was represented by the depth-weighted average N-content (0–30 cm) derived from the SoilGrids database (ISRIC, 2026), extracted at each gully centroid. This variable was selected as the most robust proxy for soil productivity based on the farmer-reported plot productivity scores collected in D2 (Section 2.2.5).

More specifically, to identify which soil variable best related to farmer-reported land productivity, all fields with a known spatial location ($n = 75$, plot-level data from D2 for which D1 and D2 were linked) were classified as either low productivity ($n = 33$), or moderate to high productivity ($n = 42$). For each field, eight SoilGrids variables were extracted: bulk density, clay, sand, silt content, cation exchange capacity, weighted N-content of the topsoil, soil organic carbon content, and pH. Each variable was tested individually using logistic regression to explain the difference between non-productive (low, 0) and productive (moderate/high, 1) fields. Given the limited dataset size, this regression was applied 1,000 times in a bootstrapping procedure, randomly splitting the data into 75% training and 25% test data in each iteration.

Weighted N-content clearly emerged as the strongest predictor, being significant ($p < 0.01$) in 96.7% of simulations (mean AUC=0.78). The second strongest variable, bulk density, was significant in only 51.9% of simulations, while all other variables scored considerably lower. A final model on the full dataset confirmed this result ($p < 0.001$, pseudo- $R^2 = 0.18$). Therefore, weighted N-content was considered as the sole physical variable describing soil fertility in our analysis.

Distance variables were derived for three spatial elements: roads, the river network, and built-up areas (Figure 16A). All distances were calculated as Euclidean distances from the gully centroid.

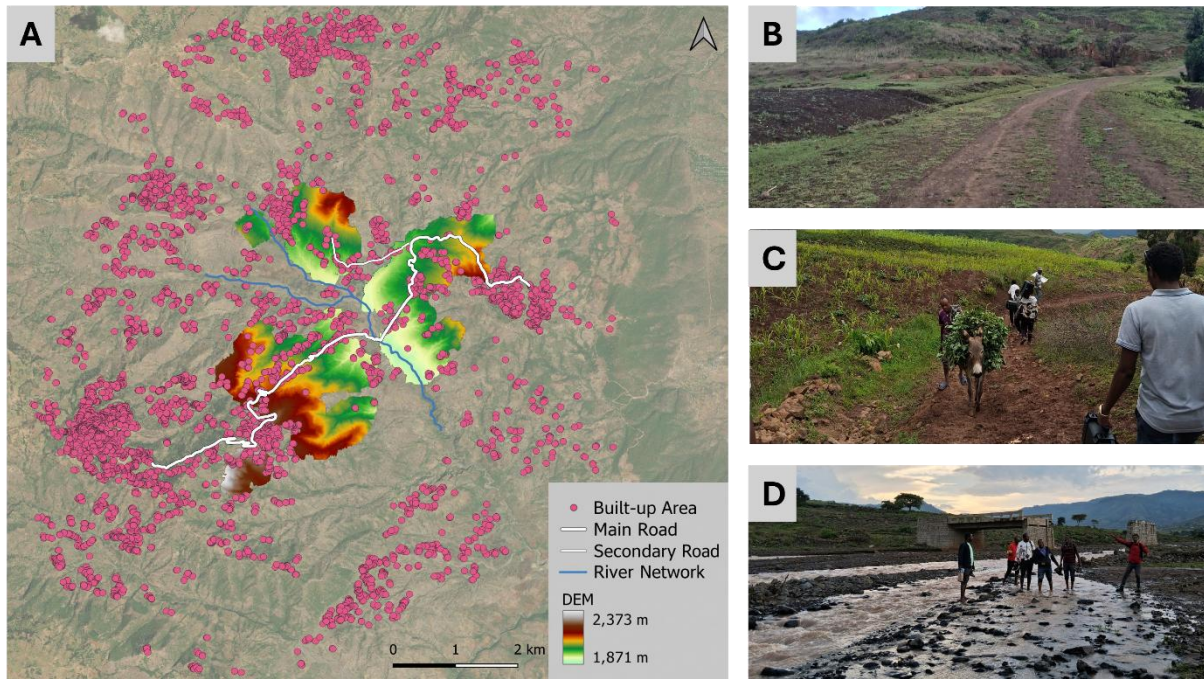


Figure 16: (A) Digital Elevation Model of the study area with key spatial proximity variables: main road, secondary road, river network, and built-up area. Background imagery: © Esri World Imagery. (B) Main road accessible by cars and motorcycles, (C) walking path and (D) river.

Two road types were digitised based on 2023 Google Earth imagery: a main road (Figure 16B) accessible by cars and motorcycles, and a secondary road accessible by motorcycle only, serving Cases 6, 7, and 8 in Morode (see Section 2.2.1, Figure 8). Walking paths (Figure 16C) were excluded as their density and highly variable accessibility conditions make them unsuitable as a meaningful accessibility reference. The distance to the nearest road was defined as the minimum of both main and secondary road distances. The river network, which flows through the study area and splits into two branches in the southern part, was mapped and treated as a single unit for distance calculations (Figure 16D), included given its role as source of stones used in the construction of check dams.

To assess proximity to farmer settlements, all buildings visible in 2023 Google Earth imagery were manually digitised by co-supervisor Y. Mekonnen within a 3 km buffer around each UAV-surveyed case area, yielding 5,858 individual building points. This approach was chosen because existing land use and land cover maps proved insufficiently detailed and reliable for identifying individual structures at this spatial scale.

Two complementary proximity variables were derived to capture settlement accessibility. First, the Euclidean distance from each gully centroid to the nearest building was calculated in QGIS as a simple measure of immediate proximity. However, a single nearby building may not reflect the broader settlement structure surrounding the gully. Therefore, Kernel Density Estimation (KDE) was additionally applied at bandwidths of 50, 100, 150, 200, 300, and 500 m in QGIS

to capture overall settlement pressure as a continuous surface across a range of spatial scales, with the KDE value extracted at each gully centroid. Gully centroids falling outside the KDE extent were assigned a value of zero.

Socio-economic variables

Socio-economic variables were derived from D2 at farmer, plot, and gully level. At farmer and plot level, GI adoption rate, the proportion of gullies containing at least one GI, was used as dependent variable, since a single farmer or plot may contain multiple gullies. At gully level, the dependent variable is the binary presence or absence of a GI. Dependent variables are summarised in Table 2.

Table 2: Overview of the dependent socio-economic variables

Level	Variable	Type	Description
Farmer/Plot	GI adoption rate	Continuous (0 – 1)	Proportion of gullies with ≥ 1 GI
Gully	GI presence	Binary	0 = untreated, 1 = ≥ 1 GI present

The socio-economic variables included at each level were selected based on their documented or hypothesised role in GI adoption, as reviewed in Section 1.3. Several variables were derived from the raw survey responses: income surplus was calculated as the difference between self-reported annual household income and expenses, total plot size as the sum of all plot sizes managed by a farmer, and travel rank by ranking each plot by reported travel time from the homestead, with rank 1 assigned to the nearest plot and equal travel times receiving equal rank. Given the exploratory nature of this analysis and the broad range of variables available from D2, a wide set of variables was initially considered at each level, as summarised in Table 3.

For gullies where GIs were present, additional questions were asked per intervention type, including multiple-choice questions as well as continuous and binary variables on implementation duration, number of attempts, and current effectiveness. These intervention-specific variables are not included in the inferential analysis but are reported descriptively.

*Table 3: Independent socio-economic variables at farmer, plot, gully and gully-sub-level; self-reported by the farmer. * indicates variables where self-reporting may substantially deviate from objective values.*

Variable	Unit	Type	Description
Farmer Level			
Age of respondent	years	Continuous	Age of respondent
Household size	count	Continuous	Total number of household members

Farming experience	years	Continuous	Years of farming experience of household head
Income	Birr	Continuous	Total annual income (past year)*
Expenses	Birr	Continuous	Total annual expenses (past year)*
Income surplus	Birr	Derived	Annual income minus annual expenses
Nr. of plots	count	Continuous	Total number of plots owned by farmer
Total plot size	ha	Derived	Sum of all plot sizes; converted from local units (1 Timad = 0.5 ha)
Prop. plots with gully	0-1	Derived	Share of farmer's plots containing at least one gully
Education level	0-4	Ordinal	0 = cannot read/write; 1 = basic literacy (no formal education); 2 = primary school; 3 = secondary school; 4 = graduate
Gender	0/1	Binary	0 = male; 1 = female
Income strategy	0/1	Binary	1 = farming only; 0 = mixed income sources
Plot Level			
Travel time	min	Continuous	Travel time from homestead to plot*
Travel rank	rank	Derived	Rank within farmer's plots by travel time; rank 1 = nearest plot; equal travel times receive equal rank
Plot yield	kg	Continuous	Total yield from plot in past year*
Plot productivity	0–2	Ordinal	0 = low productivity; 1 = moderately productive; 2 = highly productive
Years farming this plot	years	Continuous	Number of years farming in this specific plot*
Plot size	ha	Continuous	Converted from original units (Timad, ha, m ²)
Nr. Gullies in plot	count	Continuous	Number of gullies in or bordering plot
Land tenure	0/1	Binary	Land tenure status of plot 1 = certified land tenure; 0 = uncertified (including rented and shared)
Gully Level			
Gully age	years	Continuous	Years since gully was first observed*
Gully active	0/1	Binary	1 = currently active; 0 = inactive*
Gully ownership	0/1	Binary	1 = sole ownership; 0 = shared by multiple farmers
Gully impact score	0–4	Ordinal	0 = no impact; 1 = slight; 2 = moderate; 3 = severe; 4 = very severe impact of the gully on land/crop yield*
Gullies with interventions			
Motivation	-	Categorical	Multiple choice (max 3); intrinsic reasons for starting GI implementation
Who convinced farmer	-	Categorical	Multiple choice (max 3); persons or factors that influenced the adoption decision
Years practicing intervention	years	Continuous	Duration of intervention implementation*

Support received	0/1	Binary	1 = external support; 0 = no support
Type of support	-	Categorical	If support received, multiple choice; type of support received when implementing GI
Challenges encountered	-	Categorical	Multiple choice; challenges when implementing GI
Number of attempts	count	Continuous	Number of implementation attempts
Intervention currently works	0/1	Binary	1 = yes; 0 = no

2.3.2 Univariate screening of variables

Univariate screening was applied to identify which variables show significant differences in distribution between treated and untreated gullies, informing subsequent modelling (Section 2.4) and revealing broader patterns through graphical inspection. Prior to testing, the distribution of each variable was visually inspected using histograms and summary statistics to identify skewness, outliers, and missing values.

For physical variables, analyses were conducted at gully level, using binary GI presence (0 = untreated, 1 = ≥ 1 GI present) as the dependent variable. Mann-Whitney U tests were applied for continuous variables and chi-square tests for categorical ones.

Socio-economic variables at farmer and plot level were tested against GI adoption rate using Kruskal-Wallis tests for variables with three or more categories, and Mann-Whitney U tests for binary variables. Categorical variables were tested using chi-square tests. At gully level, socio-economic variables were tested against binary GI presence using Mann-Whitney U tests for continuous variables and chi-square tests for categorical variables.

2.3.3 Static predictive modelling

Building on the univariate screening, three static logistic regression models were developed to predict GI presence at gully level, with predictor effects expressed as odds ratios (Sperandei, 2014): a spatial model (based on D1), a socio-economic model (based on D2), and a combined model incorporating both spatial and socio-economic predictors.

Modelling approach

Prior to modelling, variables were assessed for skewness. Variables with an absolute skewness greater than 1 were log-transformed using $\ln(x + 1)$ to reduce the influence of extreme values. Distance variables were log-transformed regardless of skewness, as distance

effects are generally assumed to be non-linear. The few observations with $|z| > 3$ following transformation were retained as they represent genuine extreme gullies rather than measurement errors. All predictors were subsequently standardised ($z = (x - \mu) / \sigma$) to ensure odds ratios are directly comparable across variable, hereby reflecting the effect of a one standard deviation increase in each predictor

Variables were first screened using Spearman correlation against the binary GI presence indicator; variables significant at $p < 0.05$ were retained. Next, their mutual correlations were then examined using a Spearman intercorrelation matrix: when two variables showed $|r| > 0.7$, the variable with the weaker individual association with GI presence was removed. Correlations with $|r| > 0.5$, were flagged as potentially problematic and considered during variable selection.

Retained variables were then entered into a forward stepwise procedure based on the Akaike Information Criterion (AIC), which balances model fit against complexity by penalising the inclusion of variables that do not meaningfully improve the model (Akaike, 1974). Variables were added sequentially; those that did not reduce the AIC were not included in the final model. Statistical significance was assessed at three levels: $p < 0.05$, $p < 0.01$, and $p < 0.001$. A Bonferroni-corrected threshold ($0.05/k$, where k is the number of candidate variables tested) was considered, but proved less strict than $p < 0.001$ for both models; the latter therefore serves as the primary threshold. VIF values were calculated to detect multicollinearity (Alin, 2010; O'Brien, 2007); values above 5 were considered potentially problematic. For each variable in the final model, the odds ratio and 95% confidence interval are reported and visualised as a forest plot. The resulting log-odds z are converted to a predicted treatment probability as Equation 1.

$$P(treatment) = \frac{1}{1 + e^{-z}}$$

Equation 1: Logistic transformation of the log-odds (z) to a predicted treatment probability.

Model performance was evaluated using the Receiver Operating Characteristic (ROC) curve, which plots sensitivity against $1 - \text{specificity}$ across all classification thresholds. The area under this curve (AUC) provides a single measure of discriminative ability, ranging from 0.5 (random) to 1.0 (perfect) (Carter et al., 2016; Hanley & McNeil, 1982). To obtain a stable AUC estimate, 10-fold cross-validation was repeated over 5 random seeds. In each fold, 90% of observations were used for training and 10% for testing, whereby the class proportion of treated and untreated gullies was preserved across folds. This approach was preferred over a conventional train/test split given the relatively small dataset sizes (D1: $n=751$; D2: $n=988$; D3: $n=242$), for

which holdout validation is not recommended (Raschka, 2020). The mean AUC across all folds and seeds and its standard deviation are reported as the stable AUC estimate. An optimal classification threshold was determined using the Youden index ($J = \text{sensitivity} + \text{specificity} - 1$) (Youden, 1950).

Spatial logistic regression model

The spatial model was applied to the spatial dataset (D1, 751 gullies), using physical gully characteristics, spatial proximity variables, and estimated soil fertility variable as candidate predictors (Table 1, Section 2.3.1.). The fitted model was subsequently used to generate predicted treatment probabilities for all 751 gullies, providing a continuous ranking by likelihood of treatment. Additionally, gullies were classified using the Youden-optimal threshold derived from cross-validation, resulting in a categorical map showing true positives, false positives, true negatives, and false negatives.

Socio-economic logistic regression model

The socio-economic model was applied with socio-economic variables from D2, covering 988 gullies, in 516 plots, managed by 178 farmers (Table 3; Section 2.3.2). Since the analysis is conducted at the gully level, farmer- and plot-level variables are duplicated for each gully associated with that plot or farmer. This allows the examining of predictors across levels while maintaining the gully as the unit of analysis. This, however, implies that farmers managing many gullies contribute more observations to the dataset, and their farmer-level characteristics consequently carry more weight in the model. To assess whether this duplication unduly influences the results, a robustness check was performed in which only one gully was randomly selected per farmer and the model was re-run on this reduced dataset. Results were compared to those of the full dataset.

Some variables contain missing values (e.g. household surplus due to lack of reporting on the household income and expenses), which resulted in listwise deletion of observations. The effective sample size therefore depends on the variables retained in the final model and is reported alongside the model results.

Mixed logistic regression model

The mixed model combined spatial and socio-economic variables in a single logistic regression, applied to D3, the farmer-level linked dataset of 242 gullies (137 treated, 105 untreated). As described in Section 2.2.6. Only farmer-level socio-economic variables (Table 3, Section 2.3.1.) were included alongside the full set of spatial variables. Given the small sample size relative to the number of candidate variables, preselection of variables was applied

(Sperandei, 2014).. Results should, however, be interpreted with caution and are considered exploratory.

2.3.4 Spatial clustering and spatio-temporal modelling

The static models above predict GI adoption based on physical and socio-economic characteristics at a single point in time. However, informal and formal neighbourhood dynamics may also influence adoption over time (Section 1.3.5). To investigate this, a sequential analysis was conducted in three steps: first assessing whether GI adoption is spatially clustered, next whether this clustering extends through time, and finally modelling whether it reflects genuine peer effects using a discrete-time hazard model.

Spatial clustering of gully interventions

Spatial clustering of GI adoption was formally assessed using Moran's I (Equation 2). Moran's I quantifies the degree of spatial autocorrelation in a variable of interest. It therefore measures whether gullies with similar treatment status tend to cluster spatially more than expected under a random distribution (Getis, 2010). The statistic ranges from -1 to +1, where +1 indicates perfect clustering, where similar values concentrated in space, and -1 indicates perfect dispersion, e.g. a checkerboard-like pattern of alternating values. A perfect random spatial distribution would therefore be indicated by 0 (Suryowati et al., 2018). The analysis was applied to the full spatial dataset (D1, 751 gullies), using the binary GI presence indicator (0 = no intervention present, 1 = at least one intervention present) as the variable of interest.

$$I = \frac{N}{S_0} \frac{\sum_{i=1}^N \sum_{j=1}^N w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^N (x_i - \bar{x})^2}$$

Equation 2: Morans I, where N is the total number of mapped gullies in the spatial dataset (n = 751), x the value of observed variable at location i and j, $\bar{x}$ is its average of n observed variable, w_{ij} are the elements of a spatial weights matrix (W) with zeros on the diagonal, and S_0 is the sum of all weights. Based on Suryowati et al., (2018).

Since gully polygons rather than centroids were used as spatial units, distances were computed as the shortest distance between polygon boundaries rather than between central points. Gullies within the same drainage system often share or nearly touch boundaries, which would not be captured adequately using centroid distances, particularly when two separate gully systems happen to lie in close proximity to each other.

A key methodological decision in computing Moran's I is the specification of the spatial weights matrix, which defines which units are considered neighbours and how strongly they influence each other (Getis, 2010). Since no single weights configuration is universally optimal, and because the choice of w_{ij} can substantially affect the resulting autocorrelation statistic (Getis,

2010; Suryowati et al., 2018), four configurations were tested: First, queen contiguity defines two gullies as neighbours when their polygons share a boundary or vertex (Suryowati et al., 2018), effectively identifying gullies that are part of the same gully system. A small buffer of 0-10 m was applied to account for minor gaps between polygons that may have arisen during manual delineation, where adjacent sections of the same system were not mapped as fully touching. The remaining three configurations capture neighbourhood effects across broader spatial scales. K-nearest neighbours ($k = 1$ to 10) connects each gully to its k closest neighbours. Inverse distance weighting assigns weights proportional to $1/\text{distance}$ to all gullies within a defined maximum range. Lastly, a Gaussian distance kernel applies smooth exponential decay with bandwidth h (Getis, 2010).

Since Moran's I values depend on the chosen weights configuration and the dataset, they carry no fixed reference distribution and cannot be interpreted in absolute terms. The relevant question is therefore whether the observed value differs from what would be expected under spatial randomness. This was assessed using a Monte Carlo permutation test with 999 simulations, in which the observed GI presence values are randomly redistributed across gully locations (Anselin, 1995). This therefore generates an empirical reference distribution of Moran's I values under spatial randomness (Anselin, 1995). The observed statistic is then compared against this distribution, determining whether the degree of clustering exceeds a random chance of GI distribution. For each distance weights configuration, the parameter yielding the strongest statistical significance (lowest p-value from the Monte Carlo permutation test) was first identified.

Spatio-temporal clustering of gully interventions

To assess whether GI adoption is also clustered in time, Moran's I (Equation 2) was applied a second time using implementation age as the variable of interest rather than binary GI presence. A single gully can contain multiple GI points, each with its own implementation date. Therefore, the analysis was conducted at two spatial levels: At the intervention level, each of these points was treated as a separate spatial observation, yielding 91 intervention points in total (Section 2.2.6, Figure 14). At the gully level, these points were aggregated by retaining only the oldest implementation age per gully, yielding one value per gully ($n = 71$; D4). The 64 treated gullies for which no implementation date could be retrieved were excluded from both levels. The same four spatial weights configurations and parameter scan procedure as described above were applied at each level.

Discrete-time hazard modelling of gully interventions

The preceding analyses examined the degree of spatial and spatio-temporal clustering of GI adoption. However, spatial clustering alone does not reveal its underlying cause. Following Manski (1993), three mechanisms may explain such clustering. An endogenous effect occurs when farmers adopt because neighbouring farmers have already adopted. An exogenous effect arises when clustering reflects shared favourable physical or socio-economic conditions. A correlated effect refers to clustering driven by unobserved characteristics common to nearby locations.

To disentangle these effects, a discrete-time hazard model was developed (Allison, 1982; Valente, 2005). Although most commonly applied in sociology and epidemiology, this framework could also be suited to spatial adoption processes where the timing of intervention and its relationship to prior neighbourhood adoption is the central research question. In this framework, the 'hazard' refers to the probability that a gully receives its first GI in a given year. To model this, a gully-year structure is applied: rather than contributing a single row to the dataset, each gully contributes one row per year of observation, allowing the timing of adoption to be modelled explicitly (Allison, 1982). This approach extends the spatial model by incorporating a temporally explicit neighbourhood exposure variable: for each gully, this variable captures the degree to which neighbouring gullies had already received GI in the years prior to its own adoption decision (Valente, 2005).

Model building

The date of each implemented GI was recorded in years, which means that adoption timing is known only at the level of discrete annual intervals rather than as a precise date. As Allison (1982) notes, discrete-time methods are appropriate when data record only the particular interval of time in which each event occurs rather than the precise date, and are well suited to data spanning multiple years or decades, as is the case here.

Since this is a spatial neighbourhood analysis, the spatial dataset (D1) is used, extended with gully-level attributes from the socio-economic dataset (D4), as described in Section 2.2.6. Unlike the previous spatio-temporal clustering analysis, which was restricted to treated gullies with a known implementation year, this model incorporates all 751 mapped gullies, yielding three groups (Figure 17A): Group 1 ($n = 71$), treated gullies with a known implementation year; Group 2 ($n = 64$), treated gullies for which no implementation date could be retrieved; and Group 3 ($n = 616$), untreated gullies.

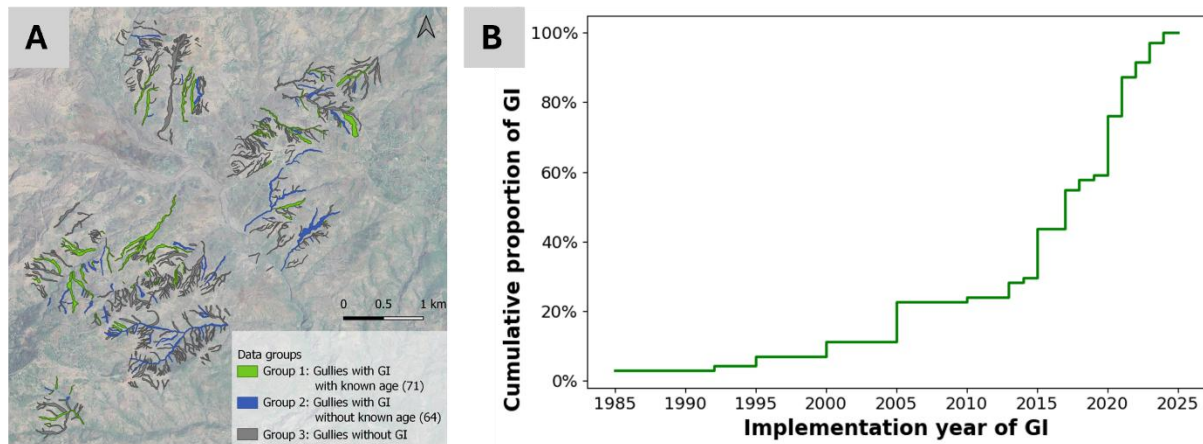


Figure 17: (A) Spatial distribution of gully data groups used in the discrete-time hazard model, showing Group 1 (intervention + known year, green), Group 2 (intervention + unknown year, blue), and Group 3 (no intervention, grey). Background imagery: © Esri World Imagery. (B) Empirical cumulative distribution function (CDF) of GI implementation years based on Group 1 gullies ($n = 71$).

A gully-year panel dataset was constructed following Allison (1982), with one row per gully per year starting from 1985 (first implementation year). Group 1 gullies contribute rows for each additional year up to (and including) their implementation year, coded as 0 in all prior years and 1 in the implementation year itself. Years after implementation are not included, as the model aims to identify the exposure threshold that triggers adoption rather than post-adoption dynamics. Group 3 gullies contribute rows from 1985 to 2025, all coded as 0. Group 2 gullies also contribute rows from 1985 to 2025, but were excluded from model fitting because their implementation year is unknown and the panel has no known endpoint for the true adoption event.

However, Group 2 gullies cannot simply be discarded: their presence may still influence the neighbourhood exposure of nearby gullies for which observations do exist. To address this, a probabilistic approach was applied. An empirical cumulative distribution function (CDF) of adoption timing was estimated from the 71 Group 1 gullies, representing for each year the fraction that had already adopted a GI, represented in Figure 17B. The key assumption is that Group 2 gullies follow the same temporal adoption distribution. The CDF value at year $t - 1$ was then used as a probabilistic adoption likelihood for Group 2 neighbours.

Once the panel dataset was constructed, the neighbourhood exposure of each gully in each year was calculated. The underlying premise is that the likelihood of a gully receiving a GI intervention increases as the proportion of neighbouring gullies where such interventions are already adopted rises (Valente, 2005; Wu et al., 2018). The exposure variable was computed for all gully-year observations in the panel. While Group 2 gullies are excluded from model fitting, they do contribute to the exposure scores of neighbouring gullies through the

probabilistic CDF approach described above. For each observation, the k nearest neighbours were identified. Each neighbour contributes to the exposure score depending on its group:

- Neighbours from Group 1 that adopted in year $t - 1$ or earlier contribute + 1; neighbours of this group that had not yet adopted a GI in year $t - 1$ contribute + 0.
- Group 2 neighbours contribute the CDF value at year $t - 1$, representing the probability that they had already adopted in that year. For example, a Group 2 neighbour contributes 0.028 to the exposure score in 1990, and 0.761 in 2020 (Figure 17B).
- Group 3 neighbours contribute + 0.

Contributions were summed and capped at 1, yielding a (potentially continuous) exposure value between 0 and 1 for each gully-year observation. This exposure variable thus captures, for each gully in each year, the adoption state of at least one of its k nearest neighbours in year $t-1$ (Valente, 2005; Wu et al., 2018). This one-year lag is applied to avoid circular results: without it, gullies adopting in the same year would mutually inflate each other's exposure score (Valente, 2005).

Selection of k -nearest neighbours

The optimal number of neighbours k to compute this exposure variable per gully per year, was determined by fitting the discrete-time hazard model for $k=1$ to 10 and selecting the value yielding the strongest model fit (lowest p -value / highest pseudo- R^2). All values of k were statistically significant ($p < 0.001$, OR ranging from around 6 to 8) (Appendix E1). $K = 6$ was selected as the best-fitting value (pseudo- $R^2 = 0.058$; p -value = $1.64e-15$, OR = 7.679 ; 95% CI [4.650-12.680]). Note that this OR reflects the unstandardised effect of moving from no (0) to full (1) neighbourhood exposure; in the multivariate models reported below, all predictors including exposure were standardised to allow direct comparison of effect sizes across variables.

Controlling for a temporal trend

However, neighbourhood exposure is by construction correlated with time. As shown in Figure 17B, more gullies adopt GI over time, so exposure scores rise inherently regardless of local diffusion. To assess whether the results reflect genuine local diffusion rather than this time trend, the analysis was also run for $k = 50$ as a robustness check. For $k \leq 10$, exposure remained significant after controlling for Year (e.g. $k = 6$: OR = 1.58, $p < 0.001$), whereas for $k = 50$ the effect became non-significant (OR = 1.36, $p = 0.17$). Note that these ORs reflect standardised predictors (z-score).

Integration into the spatial model

The exposure variable derived above (lagged neighbourhood exposure at $k = 6$) was subsequently added as an additional predictor to the spatial model (Section 2.3.3), this time using the same gully-year panel dataset of 27,402 gully-year observations across D4. Because the exposure variable is calculated per gully per year, all spatial variables were held constant across years for each gully, while only the exposure variable varies over time. While this represents a simplification of reality (i.e. gully dimensions and settlement patterns may change over time), this was necessary as no time-series for these other variables were available. Furthermore, it allows a direct comparison between models with and without exposure, isolating the additional predictive contribution of neighbourhood diffusion beyond purely spatial gully characteristics.

Four model specifications were compared:

- (A) Exposure variable only (univariate), to establish the raw diffusion signal.
- (B) Spatial variables only, refitted on the gully-year panel (27,402 rows) to serve as a direct baseline for comparison. Note that this differs from the static spatial model in Section 2.3.3: although the same predictors are used, the panel structure means each gully contributes multiple rows and the outcome is adoption in a specific year rather than adoption ever. Model statistics are therefore not directly comparable across the two frameworks.
- (C) Spatial variables and the Year variable, to assess the contribution of the general temporal trend in GI adoption independently of spatial patterns of exposure.
- (D) Exposure, Spatial variables and the Year variable, as a full spatio-temporal model.

CHAPTER 3

RESULTS

This chapter presents the results structured around the four research questions: first, it presents the spatial distribution and types of GIs, then the factors explaining adoption, followed by the static predictive models, and finally the spatio-temporal analysis.

3.1 Characteristics of the gullies and their interventions

751 gullies (D1, spatial dataset) were mapped within the UAV-surveyed area (~600 ha) based on UAV-derived orthophotos and DEMs (Section 2.2.1). 135 gullies (18%) contained at least one GI, while the remaining 616 (82%) were untreated. The spatial distribution of treated and untreated gullies is shown in Figure 18. Key morphological characteristics of the mapped gullies are summarized in Table 4.

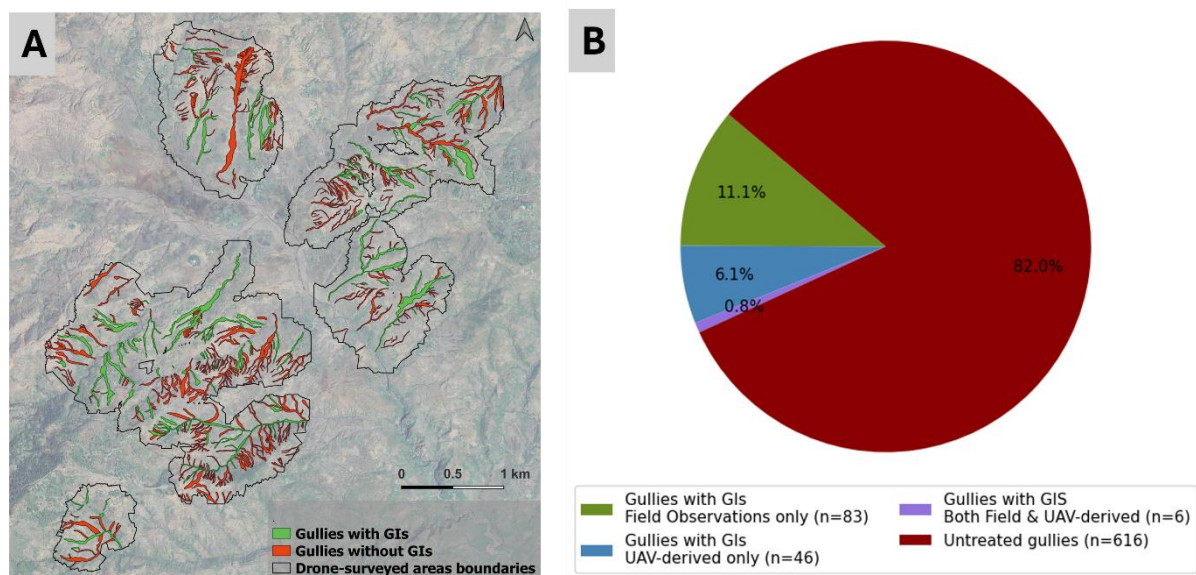


Figure 18: (A) Spatial overview of the mapped gullies in the UAV-surveyed area per treatment status. Background imagery: © Esri World Imagery. (B) Percentage of the mapped gullies per treatment status and detection method for treated gullies.

Table 4: Morphological characteristics of treated (n=135) and untreated (n=616) mapped gullies in the UAV-surveyed area

Variable	Treated gullies (n = 135)			Untreated gullies (n= 616)		
	median	mean	std	median	mean	std
Total area (m ²)	1384.73	3305.41	4789.51	500.67	1172.54	2595.56
Total length (m)	150.53	254.19	269.23	85.68	120.77	127.17
Mean width (m)	9.03	10.58	6.62	6.21	7.6	5.01
Mean slope (°)	33.07	32.6	5.94	32.42	32.36	7.16
Elevation (m a.s.l.)	2031.77	2055.47	82.35	2039.72	2052.37	78.22
Elev. diff. (m)	38.55	54.24	43.16	27.04	34.87	27.66

3.1.1 Gully interventions identified in the spatial dataset

329 individual GIs were mapped, identified through field observations (n=269) and UAV-based remote sensing (n = 60). Banana plantations (41.3%, n=136) and check dams (15.5%, n=51) are the most dominant intervention types. Individual interventions frequently co-occur within the same gully (Figure 19). Accordingly, 184 grouped interventions were measured across the 135 treated gullies. Next to banana plantations and check dams GIs, a third group encompasses trees, other crops, and grasses. For 'other crops' and 'trees', the dominant species are shown in Figure 20. Types of grasses species were not systematically recorded, but often described as 'Elephant grass'. Exact numbers are provided in Table 5, with a full overview of all observed GI in Appendix Table A1-2 and Figure A1.

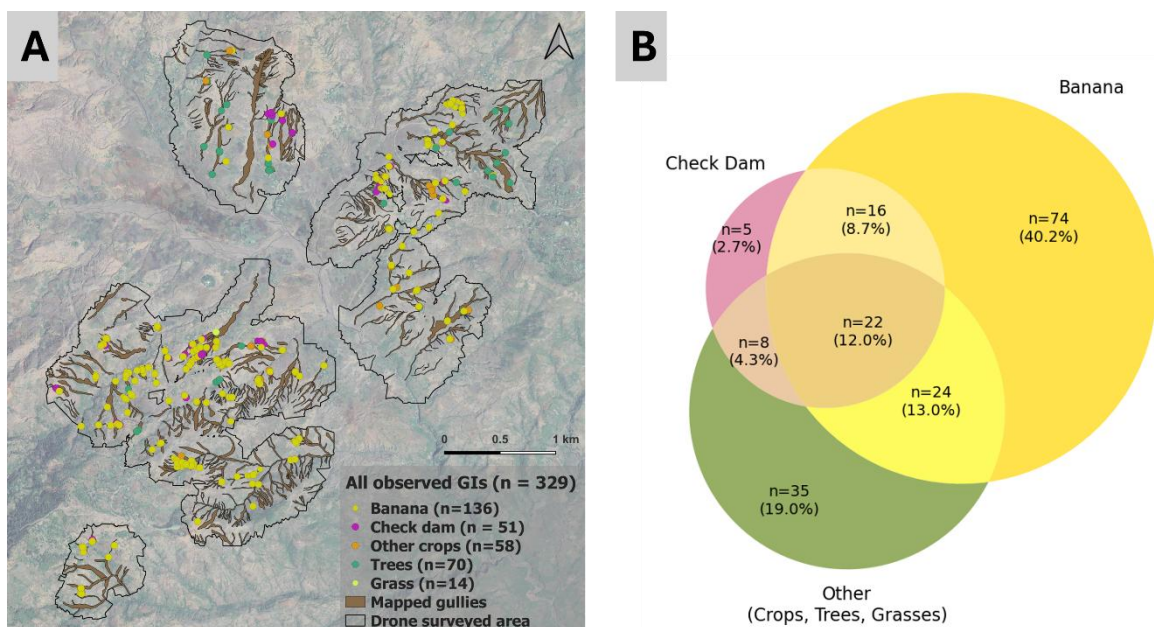


Figure 19: (A) Spatial distribution of all observed gully interventions per main category type. Background imagery: © Esri World Imagery. (B) Co-occurrence patterns of all observed gully interventions (field and UAV-derived observations) in the UAV-surveyed area.

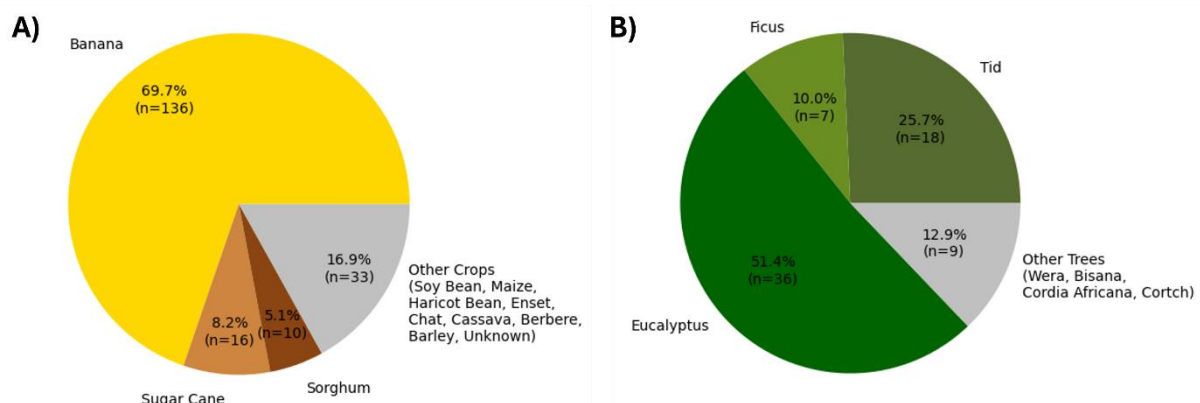


Figure 20: Distribution of (A) main crops and (B) main trees growing in gullies in the UAV-surveyed area of all observations. Note: if multiple crops/trees are present, each of them is counted separately

Table 5: Number of individual gully interventions per category: Field observed GIs, UAV-derived GIs and total observed GIs

Type of GI	No. of field observations	No. of UAV-derived observations	Total No. of observations	Percentage of total no of observed GIs
Banana	83	53	136	41.34%
Check dam	49	2	51	15.50%
Trees	67	3	70	21.28%
Other crops	56	2	58	17.63%
Grasses	14	0	14	4.30%
Total	269	60	329	

3.1.2 Gully interventions reported in the household survey

In addition, household survey data were collected from 178 farmers covering 965 plots, reporting a total of 988 gullies in 518 of those plots (D2, socio-economic data). 475 gullies (48.1%) were reported to contain at least one GI, while 513 (51.9%) remained untreated.

For the 475 treated gullies, farmers reported interventions across three broad categories: farming (n=298 gullies), physical measures (n=380 gullies), and grasses (n=174 gullies). Since multiple sub-types could be reported within each category, the total number of individual interventions recorded is higher: 1,045 items in total (Table 6). Within farming, banana was the most frequently reported crop (n=189) and was distinguished as a separate sub-category given its prevalence in both this dataset and the spatial dataset. Among the remaining 250 farming items, eucalyptus (n=93), sugar cane (n=38), and sorghum (n=22) were most common. For physical measures (n=409 items), stone check dams dominated (n=369, 90.2%), with wooden (n=31), gabion (n=1), and biological structures (n=8) making up the remainder. For grasses (n=197 items), Desho grass (n=115, 58.4%) and elephant grass (n=74, 37.6%) were most prevalent. A full overview of all individual sub-categories is provided in Appendix A3.

Table 6: Distribution of individual gully interventions in household survey

Main individual GI in survey data	Amount	Percentage
Banana	189	18.09%
Check dam	409	39.14%
Other trees/crops	250	23.90%
Grasses	197	18.84%
Total	1045	

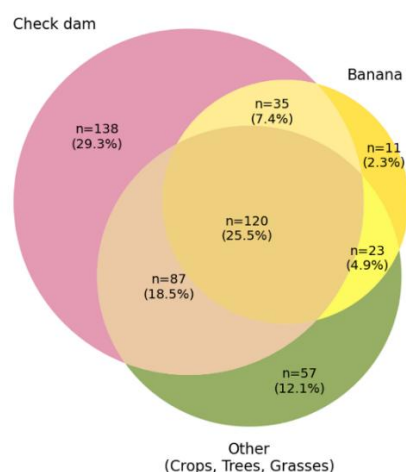


Figure 21: Co-occurrence patterns of all observed gully interventions in household survey

These categories frequently co-occur within a single gully (Figure 21). Notably, banana plantations rarely occur as the sole intervention (n=11, 2.3%), while physical measures more often appear without other interventions (n=138, 29.3%).

3.2 Variables explaining gully intervention adoption

3.2.1 Physical variables

Comparing physical characteristics (cf. Section 2.3.1; Table 1) between treated (n=135) and untreated (n=616) gullies (D1) indicates that treated gullies are significantly larger in terms of total area, total length, mean width, and elevation difference (Figure 22A–D; Table 7). Absolute elevation, slope, and weighted N-content of the topsoil (0–30 cm) show no significant difference between treated and untreated gullies (Figure 22E–G; Table 7).

Treated gullies are located significantly closer to the main road, nearest road, and nearest building than untreated gullies (Figure 22H,J,L; Table 7). Distance to the river and secondary road show no significant association with treatment status (Figure 22I,K). KDE settlement pressure, tested at radii of 50–500 m, is significantly higher around treated gullies; the two most significant radii (150 m and 200 m) are reported (Figure 22M,N; Table 7).

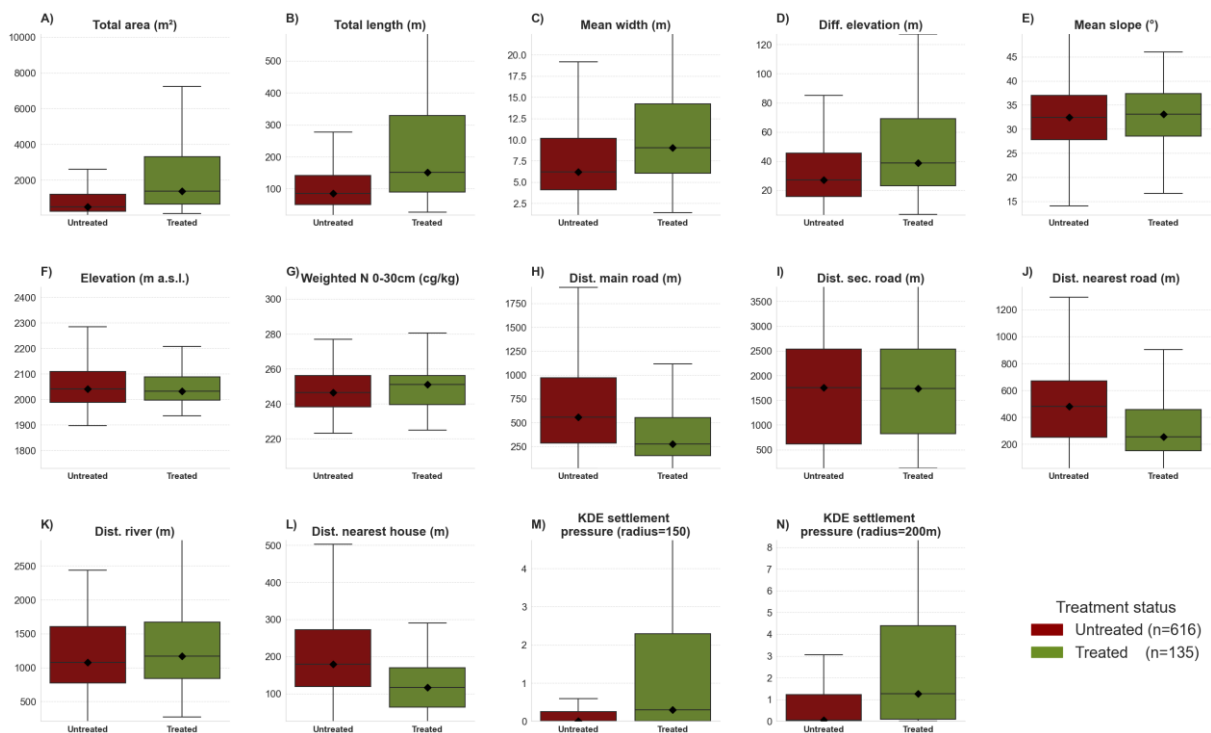


Figure 22: Boxplots of gully morphology (A-E), estimated soil fertility (G) and spatial proximity variables (H-N) for untreated (n=616) and treated (n=135) gullies. Diamonds indicate medians.

Table 7: Comparison of morphological, soil fertility and distance characteristics between treated and untreated gullies (Mann-Whitney U test). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, ns=not significant.

Variable	Treated median	Untreated median	U statistic	p-value	Significance
Total area (m ²)	1384.73	500.67	60066	5.61e-16	***
Total length (m)	150.53	85.68	59201	1.18e-14	***
Mean width (m)	9.03	6.21	55045	3.68e-09	***
Diff. Elevation (m)	38.55	27.04	54478	1.61e-08	***
Mean Slope (°)	33.07	32.42	42831	5.84e-01	ns
Elevation (m a.s.l.)	2031.77	2039.72	41551	9.90e-01	ns
Weighted N 0-30 cm (cg/kg)	250.97	246.50	38234	1.91e-01	ns
Dist. main road (m)	275.81	556.81	27799	1.57e-09	***
Dist. sec. road (m)	1734.44	1759.88	42426	7.11e-01	ns
Dist. nearest road (m)	254.65	481.64	27456	6.14e-10	***
Dist. river (m)	1169.64	1079.08	45166	1.16e-01	ns
Dist. nearest house (m)	116.24	279.65	25552	2.21e-12	***
Dist. nearest settlement cluster 150m (m)	125.46	204.57	26813	9.90e-11	***
KDE settlement pressure 150	0.03	0.00	56844	1.24e-13	***
KDE settlement pressure 200	1.26	0.05	57533	5.99e-13	***

3.2.2 Socio-economic variables

The socio-economic analysis was conducted at farmer (n=178), plot (n=965), and gully level (n=988) (D2). For each level, a distinct set of dependent and explanatory variables was considered (cf. Section 2.3.1; Table 3).

Farmer-level

The typical farmer in this study is 50 years old (median, mean = 49,52), with 35 years of farming experience (median, mean = 36.57), manages 5 plots (median, mean = 5.42), with a total area of 2.51ha (median, mean = 3.21), and lives in a household of 7 persons (median, mean = 7.69). Median annual income and expenses are both 30,000 Birr (approximately €240 at the time of the household survey), though the mean income of 42,643 Birr and expenses of 36,400 Birr suggests considerable variation. The median annual surplus is 5,000 Birr (€40 at time of the household survey, mean = 6434.84), indicating limited financial breathing room for most households.

Only 21 farmers (11.8%) had never implemented any GI, meaning that nearly 90% of all farmers have attempted at least one intervention. However, the large majority (64.0%, n = 114) only treated a selection of their gullies, while 43 farmers (24.2%) treated all their gullies. Of the 157 farmers who implemented at least one GI, 52.9% (n = 83) combined all three intervention

types, while 17.2% (n = 27) combined farming and physical interventions only, and 10.2% (n = 16) implemented physical interventions only.

No variable showed a significant association with GI adoption rate (Table 8). Farming experience (Figure 23A) shows an inverted U-shaped pattern, with the highest adoption rates among farmers with 30-35 years of experience, while both younger and older farmers show lower rates. However, the 30-35 year class contains only 14 farmers, requiring caution with the interpretation. Farmers managing more plots (Figure 23B) tend to show slightly lower adoption rates. However, this may partly reflect the construction of the rate variable itself: farmers with more plots have more gullies, resulting in more opportunities for having untreated gullies. A similar pattern is observed for total plot size (Figure 23C). For education level (figure 23D), no clear trend is visible. The apparently low adoption rate among graduates is based on only four farmers and cannot be interpreted meaningfully. Female respondents show a slightly higher median adoption rate compared to male respondents (Table 8).

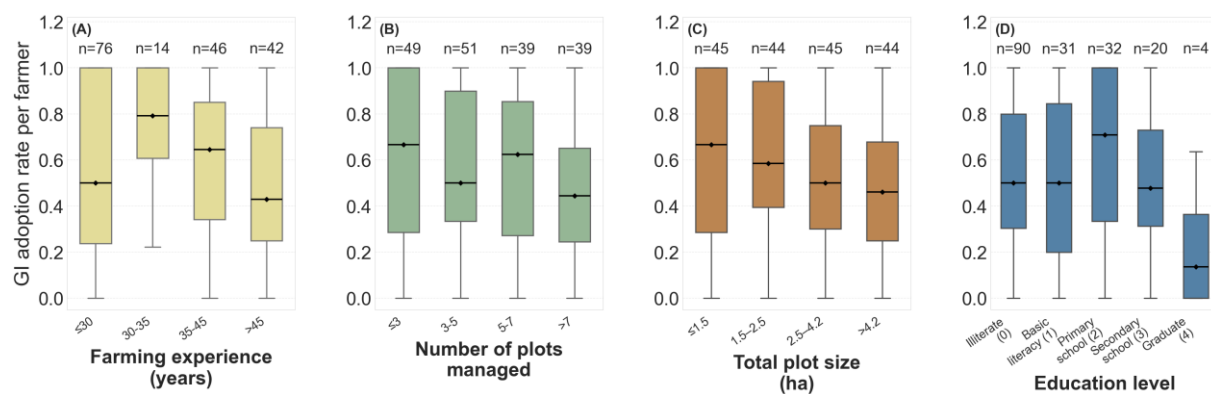


Figure 23: Gully intervention adoption rate per farmer across categories of (A) farming experience (years), (B) number of plots managed, (C) total plot size (ha) and (D) education level. Variables A-C are grouped into quartiles; education level (D) displays all response categories. Diamonds indicate medians, n per class is shown above boxes.

Table 8: Comparison of socio-economic farmer variables for gully intervention adoption rate (Kruskal-Wallis test for continuous variables, Mann-Whitney U-test for binary variables). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, ns=not significant.

Variable	Test	Statistic	p-value	Significance
Age of respondent	Kruskal-Wallis	12.316	3.40e-01	ns
Household size	Kruskal-Wallis	1.215	7.49e-01	ns
Farming experience	Kruskal-Wallis	6.494	8.99e-02	ns
Income	Kruskal-Wallis	1.305	7.28e-01	ns
Expenses	Kruskal-Wallis	1.175	7.59e-01	ns
Income surplus	Kruskal-Wallis	3.133	3.72e-01	ns
Nr. of plots	Kruskal-Wallis	4.639	2.00e-01	ns
Total plot size	Kruskal-Wallis	3.734	2.92e-01	ns
Education level	Kruskal-Wallis	7.251	1.23e-01	ns
Gender	Mann-Whitney U	2745.5	2.68e-01	ns
Income strategy	Kruskal-Wallis	1.113	5.73e-01	ns

Plot level

A typical plot managed by these farmers has a size of 0.50ha (mean = 0.69ha), a median travel time of 20 minutes from the homestead (mean = 34 minutes), a median yield of 75 kg last year (mean = 190 kg), and contains one gully (mean = 1.91). Analyses were conducted on plots containing at least one gully ($n = 516$). Of these, 240 plots (46.3%) had all gullies treated, 193 (37.3%) had none treated, and 85 (16.4%) showed mixed adoption.

Travel distance to the plot shows the strongest association with GI adoption ($p\text{-value} < 0.001$, Table 9). To visualize this relationship, travel time is converted to a travel rank per farmer, where rank 1 indicates the plot closest to the homestead. Figure 24 presents the proportion per rank of plots containing at least one GI versus those without. A clear pattern emerges: 75.6% of rank-1 plots contain at least one GI, compared to 42.4% for rank-5 plots. Mann-Whitney U test on the raw rank values confirms this association ($U = 22795.5$, $p\text{-value} = 1.61e-07$).

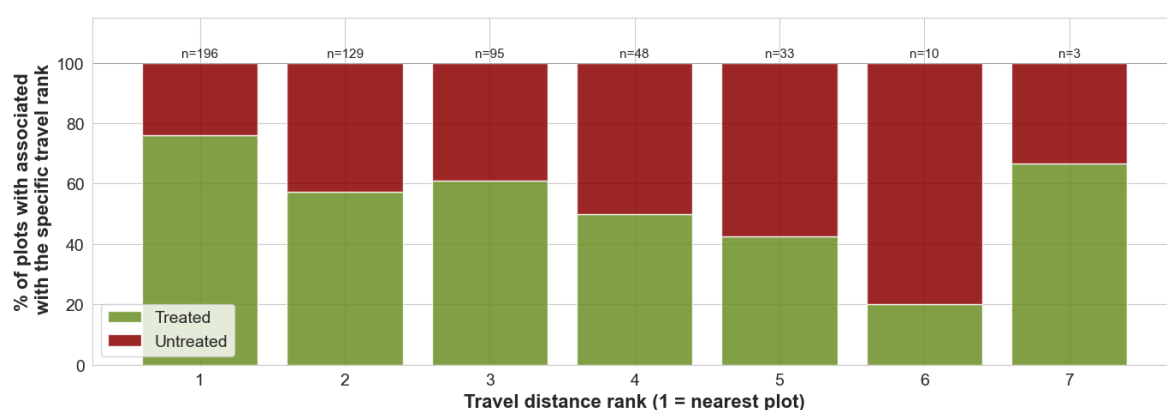


Figure 24: (A) Proportion of treated (green) and untreated (red) plots per travel distance rank (rank 1= nearest plot to homestead). Sample sizes per rank are shown above each bar. Note: tied travel times receive the same rank, resulting in $n=196$ rank-1 observations across 178 farmers for 514 plots with travel time information.

Four additional plot-level variables showed significant associations with GI adoption rate (Figure 25, Table 9). Reported plot yield in the year before the survey (Figure 25A) and self-reported productivity (Figure 25B) are both strongly significant ($p\text{-value} < 0.01$), with plots showing higher yields and perceived productivity having higher adoption rates. Years farming in the plot (Figure 25C) shows a weaker but significant association ($p\text{-value} < 0.05$): adoption rate generally increases with plot tenure but decreases again for very old plots (> 40 years). Plots containing more gullies (Figure 25D) show significantly lower adoption rates ($p\text{-value} < 0.001$), suggesting that treatment effort is spread more thinly when multiple gullies are present. Plot size, however, shows no significant association with adoption rate ($p\text{-value} = 0.124$). Plot tenure status shows no significant association with GI adoption rate ($p\text{-value} = 0.731$), likely due to limited variation as 96.1% of plots are owner-certified.

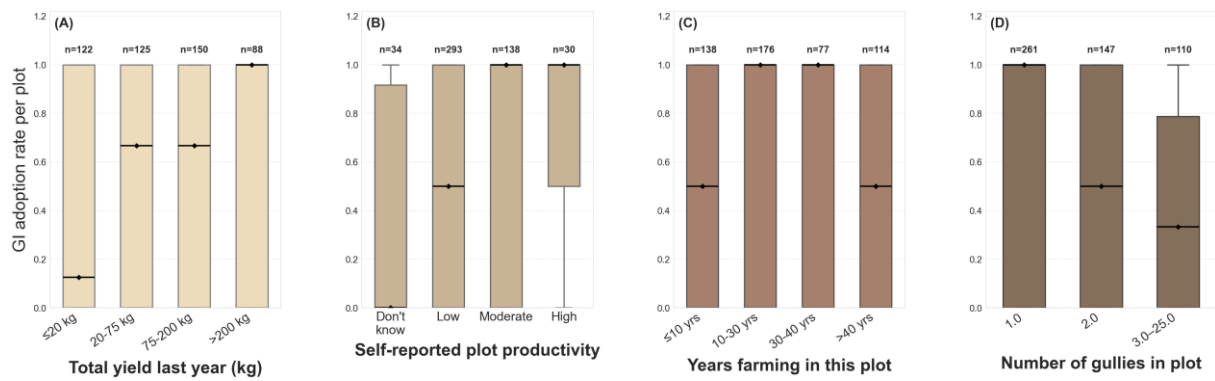


Figure 25: Gully intervention adoption rate per plot across (A) Total yield last year (kg) (B) Self-reported plot productivity (C) Years of farming in the plot (D) Number of gullies in the plot, all grouped into quartiles. Diamonds indicate medians, *n* per class is shown above boxes

Table 9: Comparison of plot-level variables for gully intervention adoption rate (Kruskal-Wallis test for continuous variables, Mann-Whitney U-test for binary variables). **p*<0.05, ***p*<0.01, ****p*<0.001, ns=not significant.

Variable	Test	statistic	p-value	Significance
Travel time	Kruskal-Wallis	38.684	2.02e-08	***
Plot Yield	Kruskal-Wallis	14.166	2.69e-03	**
Plot productivity	Kruskal-Wallis	28.978	7.90e-06	***
Years farming in plot	Kruskal-Wallis	9.417	2.42e-02	*
Plot size (ha)	Kruskal-Wallis	5.767	1.24e-01	ns
Nr. of gullies in plot	Kruskal-Wallis	23.906	6.44e-06	***
Land tenure	Mann-Whiney U	4771.0.	7.30e-01	ns

Gully level

At the gully level, three variables show significant associations with GI presence (Table 10). The median gully age is 25 years (mean = 35.41). Treated gullies are significantly younger than untreated gullies (*p*-value = 0.003; Figure 26A). Gully ownership also matters: gullies owned by a single farmer are more likely to be treated than shared gullies, which are crossing or bordering plots of multiple farmers (*p*-value < 0.001; Figure 26B). In addition, treated and untreated gullies differ significantly in perceived impact score (*p*-value < 0.001; Figure 26C), though the distribution is not monotonic: adoption appears highest for moderate to severe impact gullies, while very severely affected gullies show comparatively lower treatment rates. Whether a gully is currently considered active shows no significant association with treatment status.

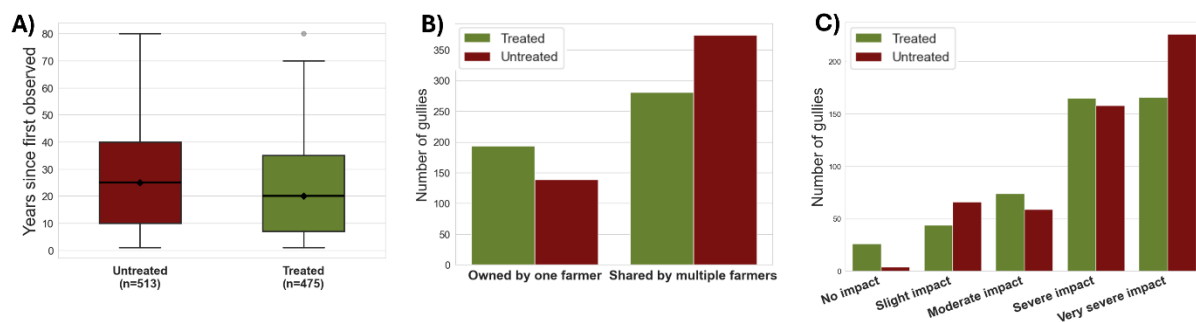


Figure 26: Gully-level characteristics by treatment status for (A) Years since first observation of gully (Diamonds indicate medians; n shown on x-axis), (B) gully ownership and (C) perceived impact score shown as histograms where red = untreated (n = 513) and green is treated (n=475).

Table 10: Comparison of gully-level socio-economic variables between treated (n=475) and untreated (n=513) gullies (Mann-Whitney U for continuous variables, Chi-square for categorical variables $p < 0.05$, $**p < 0.01$, $***p < 0.001$, ns=not significant).

Variable	Test	Statistic	p-value	Significance
Gully age	Mann-Whitney U	108649.5	3.17e-03	**
Gully active	Chi-square	0.044	8.34e-01	ns
Gully ownership	Chi-square	20.247	6.80e-06	***
Gully impact score	Chi-square	30.143	4.58e-06	***

Farmer perceptions and experiences of gully interventions

When stating to have implemented GIs in a specific gully, farmers were asked about their motivations and sources of influence per intervention type implemented, with up to three answers allowed per question. Personal motivation to rehabilitate is the most frequently cited reason across all three types, indicating that GI adoption is largely self-initiated rather than externally imposed (Figure 27A). Similarly, own decision is reported as the primary source of influence (Figure 27B). However, multiple reasons are commonly reported (avg. 1.6/1.7 for motivation; 1.3/1.4 for influence). Government/NGO encouragement ranks second in both figures, suggesting that while adoption is primarily autonomous, institutional support also plays a notable role.

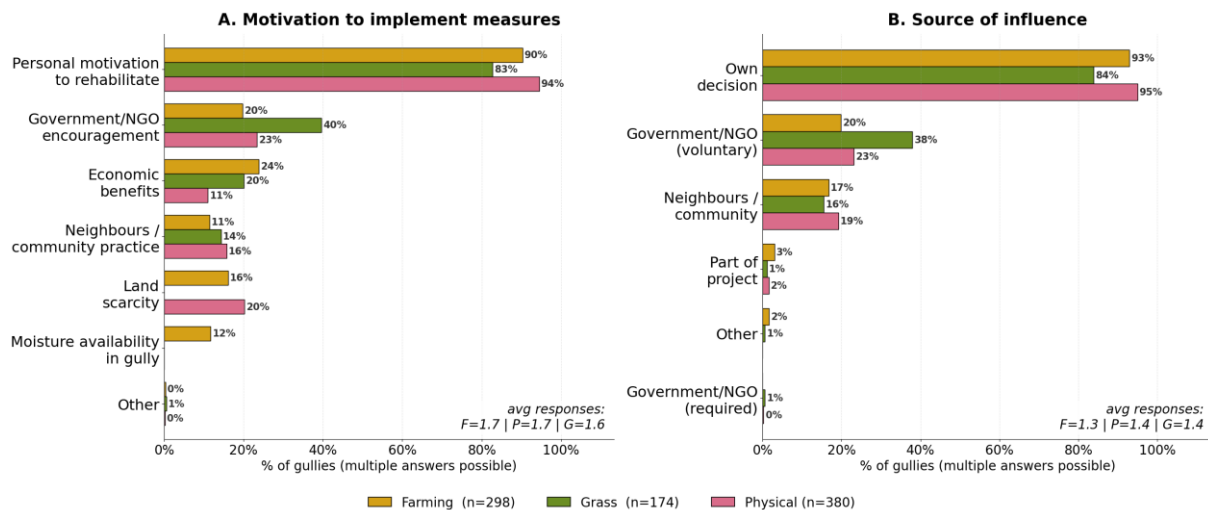


Figure 27: (A) Reported motivations and (B) sources of influence for implementing gully interventions, compared across farming (n=298), grass (n=174) and physical (n=380) intervention types. Values show the percentage of gullies within each intervention type where this answer was selected. Multiple answers were allowed per question. Average number of responses per gully is shown in each panel.

Farmers report reduced soil loss and gully rehabilitation most frequently as benefits across all three types, closely followed by decreased sediment flow (Figure 28A). Notably, economic benefits are reported as a positive impact for a relatively high proportion of farming interventions (53%), despite being less frequently cited as an initial motivation (Figure 27A, 24% for farming). For grass interventions, fodder for livestock is a notably high benefit (72%). Physical interventions are associated with considerably more challenges than farming or grass interventions, reflected in the higher average number of responses per gully ($P = 2.9$ vs $F = 1.8$, $G = 1.7$). The main challenges for physical interventions include poor soil conditions, resource limitations, lack of technical support, lack of regular maintenance, and inadequate design (Figure 28B).

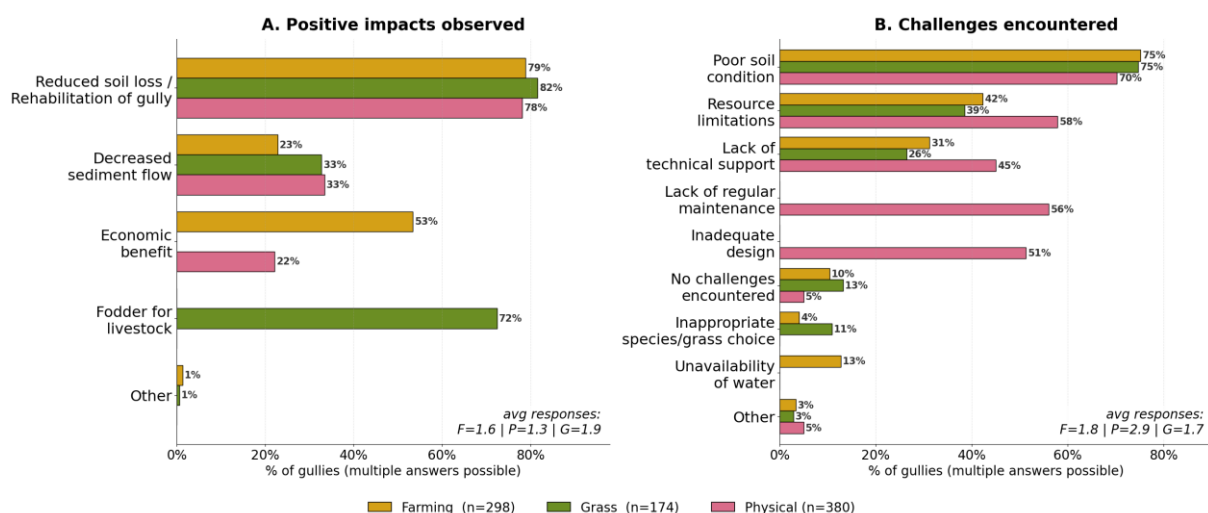


Figure 28: Reported positive impacts (A) and challenges encountered (B) during gully intervention implementation, compared across farming (n=298), grass (n=174) and physical (n=380) intervention types. Values show the percentage of gullies within each intervention type where this answer was selected. Multiple answers were allowed per question. Average number of responses per gully is shown in each panel.

Farmers who implemented at least one GI ($n = 157$) were additionally asked to rank five broad factor categories by perceived importance in their GI adoption decision (lower rank = more important). 137 farmers completed this question, of whom three reported no in-gully GIs but did implement upslope measures. Figure 29 presents the overall ranking across these five categories (Figure 29A), as well as the subcategory rankings within each broad category (Figure 29B-F).

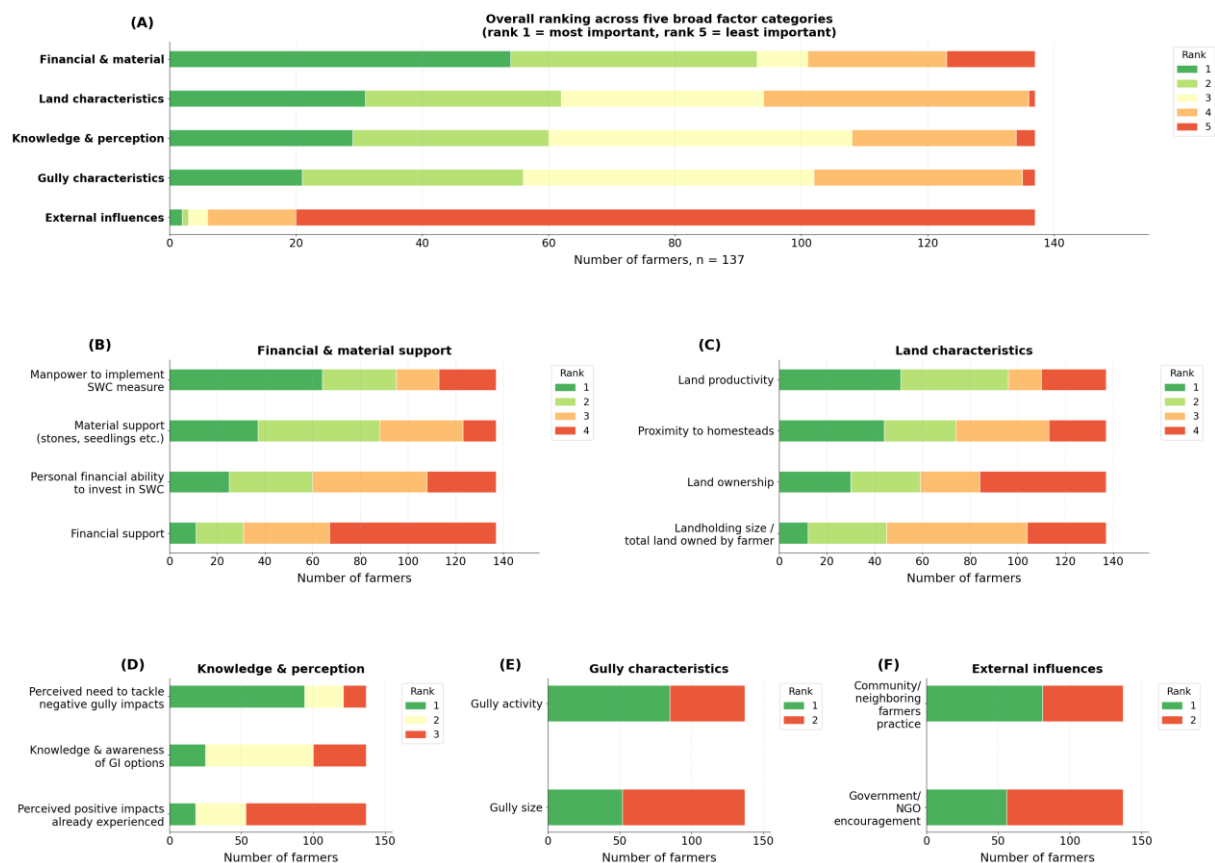


Figure 29: Distribution of assigned ranks (lower rank=more important) for factors influencing gully intervention adoption decisions, reported by farmers who answered this question ($n=137$) with (A) overall ranking across five broad factor categories and (B-F) sub-ranking: (B) financial and material support, (C) land characteristics, (D) knowledge & perception, (E) gully characteristics and (F) external influences.

Financial and material factors are ranked most important by the largest share of farmers (Figure 29A). Within this category, manpower and material support emerge as the most influential subcategories, while general financial support is considered less important (Figure 29B). Land characteristics, knowledge and perception, and gully characteristics show broadly similar overall rankings (Figure 29A). Within land characteristics, plot productivity ranks highest, followed by proximity to the homestead, land ownership, and total land size (Figure 29C). For knowledge and perception, perceived need to tackle negative gully impacts is ranked most important, followed by general awareness. Perceived positive impacts already experienced rank lowest (Figure 29D). For gully characteristics, gully activity ranks higher than

gully size (Figure 29E), contrasting with the physical model where gully size is a strong predictor of treatment. External influences are ranked least important by around 85% of respondents (Figure 29A). Within this category neighbourhood influence ranks above government/NGO encouragement (Figure 29F).

Figure 30A presents the GI types farmers expressed to most interested in for adopting in the future, with a distinction between farmers who already implement GIs (n=157), and those who did not (n=21). For the most common GI types in this study (crop planting and stone check dams), interest levels are broadly similar between both groups, suggesting high potential to expand these practices among non-adopters. Notably, 86% of non-adopters express interest in at least one GI type, suggesting openness to future adoption.

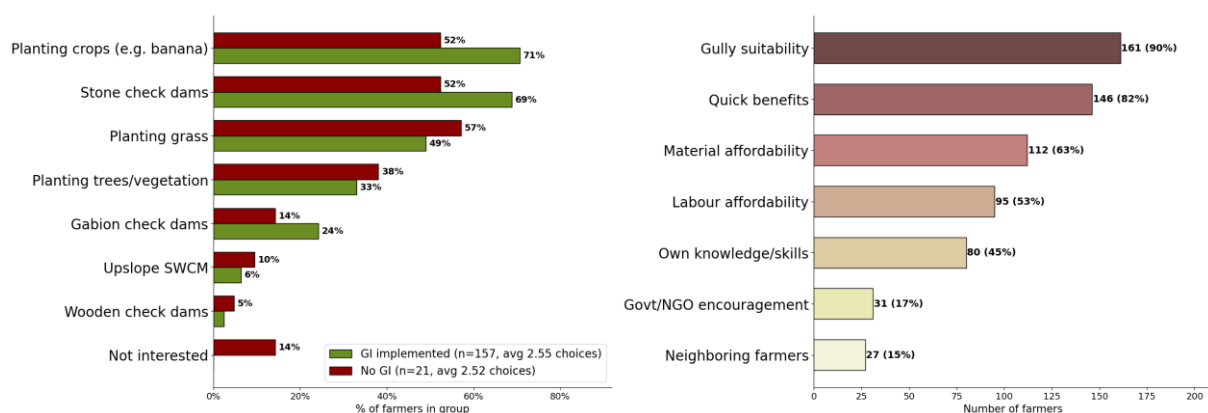


Figure 30: Future GI intentions among farmers who currently implement GIs (n = 157) and those who do not (n = 21): (A) percentage of farmers in each group expressing interest in each GI type (max 3 choices per farmer; values can sum to >100%); (B) overall reasons for preferring specific GI types, expressed as the percentage of all 178 farmers who mentioned each reason at least once, regardless of how many GI types they selected that reason for.

Figure 30B shows the overall reasons farmers gave for their preferred future GI choices. Since reasons expressed were similar across different future GI types, reasons are expressed as the percentage of all 178 farmers who mentioned a reason at least once across all selected GI types. Gully suitability is most frequently cited (90%), followed by quick benefits (82%), material affordability (63%), labour affordability (53%), and own knowledge (45%). Government/NGO encouragement (17%) and influence from neighbouring farmers (15%) are mentioned least frequently.

Lastly, 14 farmers attended a gully rehabilitation workshop, likely one organized by the AMU-IUC project. Of these, 93% reported that participation changed their approach to GI implementation, and all but one reported an increase in GI knowledge.

3.3 Predictive static modelling of gully intervention priority

3.3.1 Spatial logistic regression model

The spatial logistic regression model was fitted on the full spatial dataset (D1, 751 gullies), using physical gully characteristics, spatial proximity variables, and estimated soil fertility as candidate predictors. Following the variable screening procedure described in Section 2.3.2, significant univariate Spearman correlations between physical variables and gully treatment status are shown in Table 11. All significant variables were log-transformed. Non-significant variables and less-significant KDE settlement pressure radii are listed in Appendix Table B1.

Table 11: Univariate Spearman correlation coefficients between physical variables and gully treatment status (n=751). Only significant variables ($p < 0.05$) are shown. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Variable	Spearman r	p-value	Significance
log(Total area)	0.296	1.28e-16	***
log(Total length)	0.282	3.51e-15	***
log(Mean width)	0.215	2.48e-09	***
log(Elev. diff.)	0.206	1.16e-08	***
log(Dist. Nearest Road)	-0.226	3.80e-10	***
log(Dist. Main Road)	-0.220	1.02e-09	***
log(KDE settlement pressure 200m)	0.263	2.43e-13	***
log(KDE settlement pressure 150m)	0.271	4.46e-14	***
log(Dist. Nearest House)	-0.256	9.78e-13	***

Based on intercorrelation screening (Appendix Figure B1), Log(Total area) was retained over Log(Total length), Log(Mean width), and Log(Elev. diff.); Log(Distance to nearest road) over Log(Distance to main road); and Log(KDE settlement pressure 150m) over Log(KDE settlement pressure 200m) and Log(Distance to nearest house). KDE settlement pressure 150m was replaced by KDE settlement pressure 200m in the final run, as this yielded a lower AIC and higher AUC.

The final spatial logistic regression model retains three variables: log(Total area), Log(Distance to nearest road), and Log(KDE settlement pressure 200m). The linear predictor is expressed as Equation 3:

$$z = -1.9246 + (0.8926 * \text{Log}(\text{Total area})) + (-0.3998 * \text{Log}(\text{Dist. nearest road})) + (0.5744 * \text{log}(\text{KDE settlement pressure 200m}))$$

Equation 3: Linear predictor for the final spatial logistic regression model (standardised predictors, $n=751$, where z is the log-odds of treatment. predicted probabilities are obtained via Equation 1 (Section 2.3.3).

All three predictors have highly significant odds ratios (OR) at $p < 0.001$. These ORs express the multiplicative change in treatment odds associated with a one standard deviation increase in each log-transformed predictor. Therefore, if a gully increases by one standard deviation in the log-transformed value of a given characteristic, its odds of being treated change by the corresponding factor. These odds ratios indicate that larger gullies (OR = 2.44), gullies located closer to roads (OR = 0.67), and gullies in greater proximity to settlements (OR = 1.78) are substantially more likely to be treated (Figure 31A, Table 12). VIF values confirm the absence of multicollinearity.

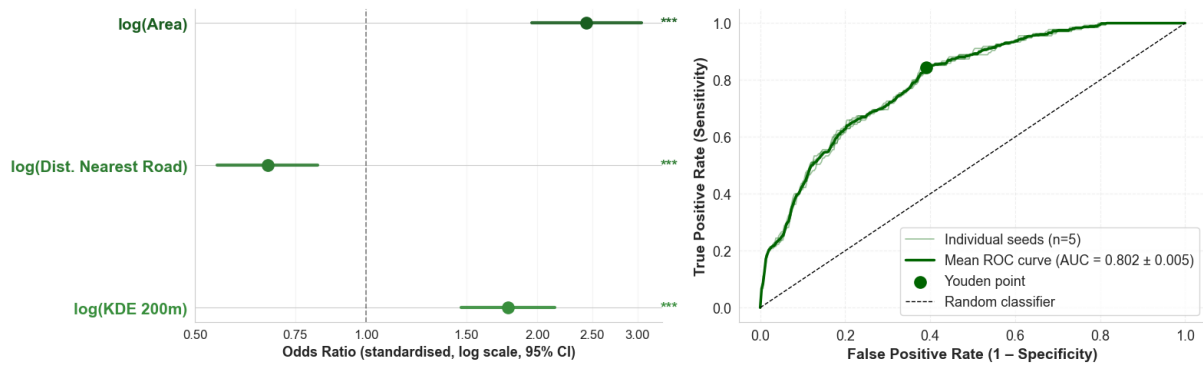


Figure 31: (A) Standardised odds ratios (OR) with 95% confidence intervals for the final spatial logistic regression model ($n=751$). All predictors are z-score standardised; ORs reflect a one standard deviation increase (log-transformed). (B) Cross-validated ROC curve (10-fold, 5 seeds), $AUC=0.802\pm0.005$ and Youden point (0.126). * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table 12: : Final spatial logistic regression model odds ratios (OR), 95% confidence intervals, p-values, significance at * $p<0.05$, ** $p<0.01$, *** $p<0.001$, ns = not significant and VIF scores ($n=751$).

Variable	OR	95% CI	p-value	Significance	VIF
log(Dist. Nearest road)	0.670	[0.547 - 0.822]	1.15e-04	***	1.067
log(Total area)	2.441	[1.955 - 3.050]	3.64e-15	***	1.009
log(KDE settlement pressure 200m)	1.776	[1.467 - 2.150]	3.82e-09	***	1.076

As shown in Table 13 and Figure 31B, the model achieves a cross-validated AUC of 0.802 ± 0.005 , indicating acceptable to good discriminative performance (Carter et al., 2016). The pseudo- R^2 of 0.197 falls just below the 0.2-0.4 range considered a good fit for logistic regression (Wilson et al., 2005), indicating acceptable explanatory power.

Table 13: Spatial logistic regression model statistics: sample size (n), AIC, pseudo-R² and cross-validated AUC

n	751
AIC	576.25
Pseudo-R ²	0.197
Cross-validated AUC	0.802 ± 0.005

Given that the spatial model is applied to the full spatial dataset (D1, n=751), model predictions can be mapped across the entire study area as a continuous treatment probability per gully (Figure 32). The spatial distribution of classification outcomes and a summary of model performance at the Youden threshold (0.126) are provided in Appendix Table and Figure B2.

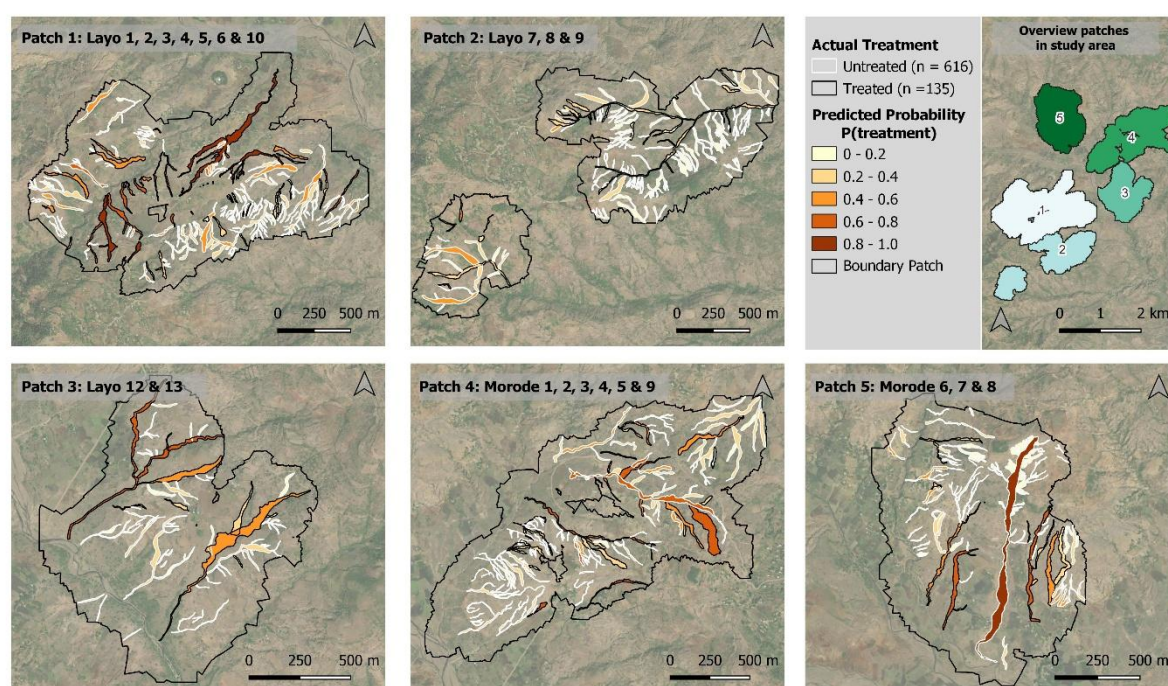


Figure 32: predicted treatment probability per gully across the study area (filled polygons), grouped in patches of the mapped cases. Outline colour indicates actual treatment status (White=untreated, Black=treated). Higher predicted probabilities indicate greater likelihood of gully intervention adoption based on the spatial logistic regression model. Background imagery: © Esri World Imagery.

3.3.2 Socio-economic logistic regression model

The socio-economic logistic regression model was fitted on the socio-economic dataset (D2). In total, 22 variables were tested across three hierarchical levels: gully, farmer, and plot. Variables with skewness greater than 1 were log-transformed, including household size, income, surplus, total plot size, plot yield, individual plot size, and number of gullies in the plot. Significant univariate Spearman correlations are shown in Table 14, non-significant variables are listed in Appendix Table C1.

Table 14: Univariate Spearman correlation coefficients between socio-economic variables and gully treatment status (n varies per variable due to listwise deletion). Variables are grouped by hierarchical level (farmer, plot, gully); only significant associations ($p < 0.05$) are shown. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Variable	Level	n	Spearman r	p-value	Significance
log(Total plot size)	Farmer	988	-0.114	3.23e-04	***
Gender	Farmer	988	0.116	2.61e-04	***
log(Income surplus)	Farmer	910	0.104	1.63e-03	**
Nr. of plots	Farmer	988	-0.086	6.75e-03	**
Income farming only	Farmer	988	0.079	1.36e-02	*
Travel rank	Plot	981	-0.206	7.52e-11	***
log(Nr. gullies in plot)	Plot	988	-0.205	8.66e-11	***
log(Plot yield)	Plot	933	0.166	3.45e-07	***
Plot productivity	Plot	865	0.135	6.76e-05	***
log(Plot size)	Plot	988	-0.107	7.94e-04	***
Travel time	Plot	981	-0.200	2.86e-10	***
Years farming this plot	Plot	981	0.102	1.40e-03	**
Gully ownership	Gully	988	0.145	4.53e-06	***
Gully age	Gully	988	-0.094	3.13e-03	**
Gully impact score	Gully	988	-0.090	4.43e-03	**

Among intercorrelated variables, travel rank was retained over travel time and number of plots, and log(individual plot size) over log(total plot size), based on correlation screening (Appendix figure C1), and subsequently removed when raising AIC or not significant at the multivariate level.

Gully age presented a borderline case: although its inclusion marginally lowered the AIC, the effect was limited and the confidence interval approached 1 (OR = 0.858, 95% CI [0.738–0.998], $p = 0.047$), indicating limited practical relevance. It was therefore excluded from the final model.

The final model retains five variables: gully ownership, travel rank, log(N gullies in plot), log(surplus), and log(plot yield). The dataset contains 854 gullies instead of 988 (D2), after listwise deletion of missing values on retained variables. The linear predictor is expressed as Equation 4:

$$z = 0.0295 + (0.5350 * \text{Gully ownership}) + (0.2835 * \log(\text{Income surplus})) - (0.5088 * \text{travel rank}) + (0.3257 * \log(\text{Plot yield})) - (0.4029 * \log(\text{Nr. gullies in plot}))$$

Equation 4: Linear predictor for the final socio-economic logistic regression model (standardised predictors, $n=854$). z represents the log-odds of treatment; predicted probabilities are obtained via Equation 1 (Section 2.3.3).

The odds ratios (Figure 33A, Table 15) indicate that gullies owned by a single farmer (OR = 1.71), located in plots with higher self-reported yields (OR = 1.39) and higher household surplus (OR = 1.33), are more likely to be treated. Conversely, plots located relatively further

away from the homestead (cf. travel rank (OR = 0.60) and plots containing more gullies (OR = 0.67) show lower treatment likelihood.

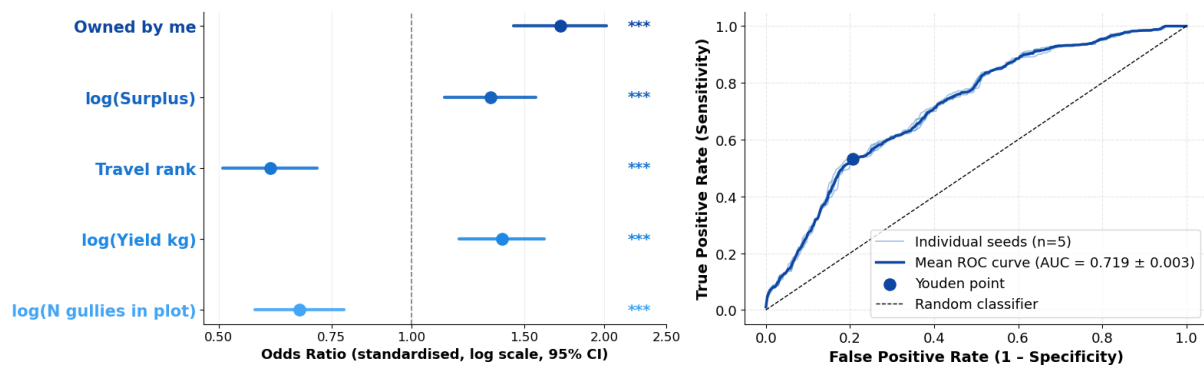


Figure 33: A) Standardised odds ratios (OR) with 95% confidence intervals for the final socio-economic logistic regression model ($n = 854$). All predictors are z-score standardised; ORs reflect a one standard deviation increase (log-transformed where applicable). (B) Cross-validated ROC curve (10-fold, 5 seeds), $AUC=0.719 \pm 0.003$ and Youden point (0.610). * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table 15: Final socio-economic logistic regression model: odds ratios (OR), 95% confidence intervals, p-values, and VIF scores ($n = 854$). * $p<0.05$, ** $p<0.01$, *** $p<0.001$, ns = not significant

Variable	Level	OR	95% CI	p-value	Significance	VIF
Gully ownership	Gully	1.707	[1.445 - 2.018]	3.34e-10	***	1.188
log(Income surplus)	Farmer	1.328	[1.126 - 1.566]	7.60e-04	***	1.236
Travel rank	Plot	0.601	[0.508 - 0.712]	3.81e-09	***	1.149
log(Plot yield kg)	Plot	1.385	[1.188 - 1.614]	3.05e-05	***	1.103
log(Nr gullies in plot)	Plot	0.668	[0.569 - 0.785]	8.29e-07	***	1.091

The model achieves a stable AUC of 0.719 ± 0.003 (figure 33B), indicating reasonable discriminative performance (Carter et al., 2016). The pseudo- R^2 of 0.120 falls below the 0.2-0.4 range considered a good fit (Wilson et al., 2005), reflecting the inherently complex nature of socio-economic adoption decisions. The 1-gully-per-farmer check achieves a stable AUC of 0.729 ± 0.009 . Model statistics are summarised in Table 16.

Table 16: Socio-economic logistic regression model statistics: sample size (n), AIC, pseudo- R^2 and cross-validated AUC and cross-validated 1-gully-per-farmer AUC

n	854
AIC	1053.90
Pseudo- R^2	0.1198
Cross-validated AUC	0.719 ± 0.003
Cross-validated AUC (1-per-farmer)	0.729 ± 0.009

3.3.3 Mixed logistic regression model

The mixed logistic regression model was fitted on the farmer-level linked dataset (D3, n = 242; 137 treated, 105 untreated gullies), combining physical gully characteristics with farmer-level socio-economic variables. After screening, only two variables were retained for the final model: log(Area) and log(KDE 200), where the linear predictor is expressed as Equation 5 and model statistics given in table 17. Univariate Spearman correlations for all candidate variables are provided in Appendix D1.

$$Z = 0.4012 + 1.1446 * \log(\text{Total area}) + 0.5192 * \log(\text{KDE settlement pressure 200m})$$

Equation 5: Linear predictor for the final mixed logistic regression model (standardised predictors, n = 242). z represents the log-odds of treatment; predicted probabilities are obtained via Equation 1 (Section 2.3.3.).

Table 17: Mixed logistic regression model statistics: sample size (n), AIC, pseudo-R² and cross-validated AUC (10-fold)

n	242
AIC	268.75
Pseudo-R ²	0.2068
Cross-validated AUC	0.779 ± 0.091

As the mixed model is effectively a constrained version of the physical model, retaining only physical predictors due to lower data availability, and achieves a lower cross-validated AUC (0.779 vs. 0.802) on a substantially smaller sample, it is not considered further.

3.4 Spatio-temporal clustering and modelling of gully intervention adoption

3.4.1 Spatial clustering

GI adoption shows significant positive spatial autocorrelation across all four weight configurations (Moran's I = 0.24-0.41, p=0.001), indicating that treated gullies tend to cluster spatially rather than being randomly distributed across the landscape. For each configuration, the parameter yielding the strongest result (lowest p-value and highest Moran's I within each configuration) across the tested range was selected (Figure 34).

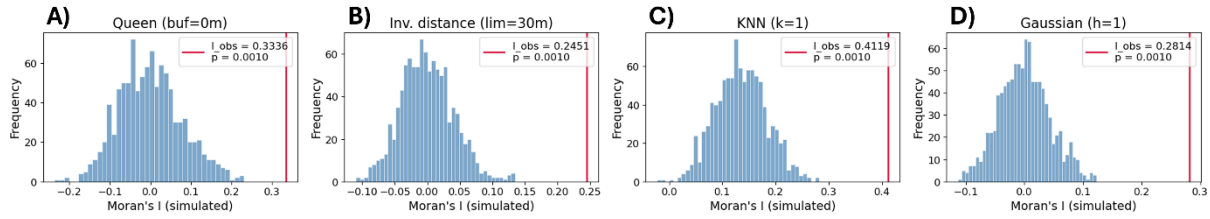


Figure 34: Monte Carlo permutation test results (999 simulations) for spatial autocorrelation of GI adoption under four spatial weight configurations: (A) Queen contiguity (buffer=0m), (B) Inverse distance (limit=30m), (C) KNN ($k=1$), (D) Gaussian ($h=1$) for the spatial dataset ($n=751$). For each configuration, the parameter yielding the lowest p -value was selected from a parameter scan. The red line indicates the observed Moran's I (I_{obs}); $p=0.001$ for all configurations.

3.4.2 Spatio-temporal clustering

Temporal clustering was analysed at two spatial levels: individual GI points ($n=91$, Figure 35) and polygon-level aggregation based on the oldest recorded GI per gully ($n=71$, Figure 36). In both cases, Monte Carlo simulations showed no significant temporal clustering. However, observed Moran's I values consistently exceed the mean of the simulated distribution, and in several cases p -values approach significance (individual points: inverse distance $p=0.072$, Gaussian $p=0.083$; polygon level: all $p>0.14$), though this pattern remains statistically inconclusive.

Temporal signal is somewhat stronger at the individual point level than at the polygon level, likely because aggregating to the oldest GI per gully reduces the available information. The 64 treated gullies with unknown implementation dates were excluded from this analysis, which may introduce additional uncertainty: gullies that appear spatially isolated may in fact be clustered with GIs of unknown timing.

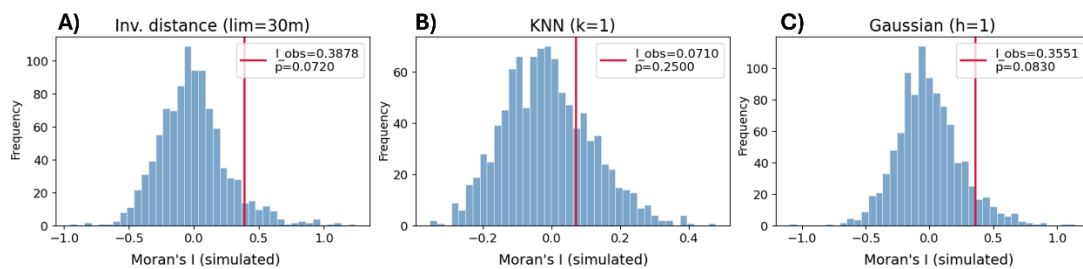


Figure 35: Monte Carlo permutation test results (999 simulations) for spatial autocorrelation of GI adoption implementation age under three spatial weight configurations: (A) Inverse distance (lim=30m), (B) KNN ($k=1$), (C) Gaussian ($h=1$) for the gully-level-linked individual unique measures ($n=91$). For each configuration, the parameter yielding the lowest p -value was selected from a parameter scan. The red line indicates the observed Moran's I (I_{obs}).

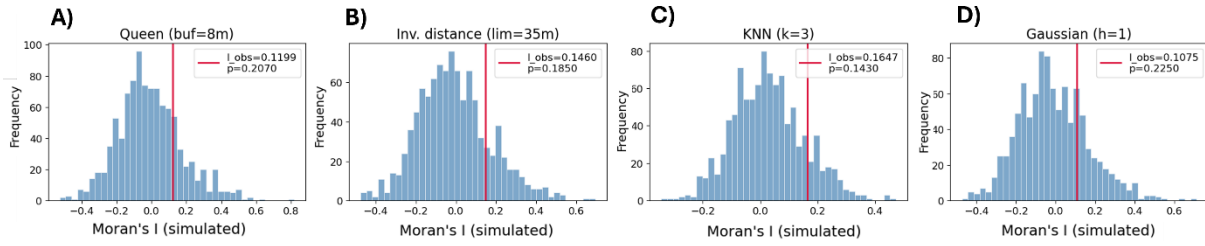


Figure 36: Monte Carlo permutation test results (999 simulations) for spatial autocorrelation of GI adoption implementation age under four spatial weight configurations: (A) Queen contiguity (buffer=8m), (B) Inverse distance (limit=35m), (C) KNN ($k=3$), (D) Gaussian ($h=1$) for the gully-level linked gullies with gully interventions ($n=71$). For each configuration, the parameter yielding the lowest p -value was selected from a parameter scan. The red line indicates the observed Moran's I (I_{obs}).

3.4.3 Discrete-time hazard modelling

The discrete-time hazard model was fitted on the gully-level linked dataset extended with all spatial gullies (D4), structured as a gully-year panel of 27,402 gully-year rows across 687 gullies, with 71 adoption events. Based on the k -scan described in Section 2.3., $k = 6$ was selected as the optimal neighbourhood size (pseudo- $R^2 = 0.058$, OR = 7.68, $p < 0.001$). Four progressive model specifications were subsequently compared, all fitted on the same gully-year panel (27,402 gully-year rows, 687 gullies, 71 events). All predictors were standardised prior to modelling; odds ratios reflect the effect of a one standard deviation increase in each predictor and are directly comparable across variables. Note that neighbourhood exposure and year are not log-transformed, while $\log(\text{Total area})$ and $\log(\text{KDE settlement pressure 200m})$ are. Results are presented in Figure 37-38, and Tables 18-19.

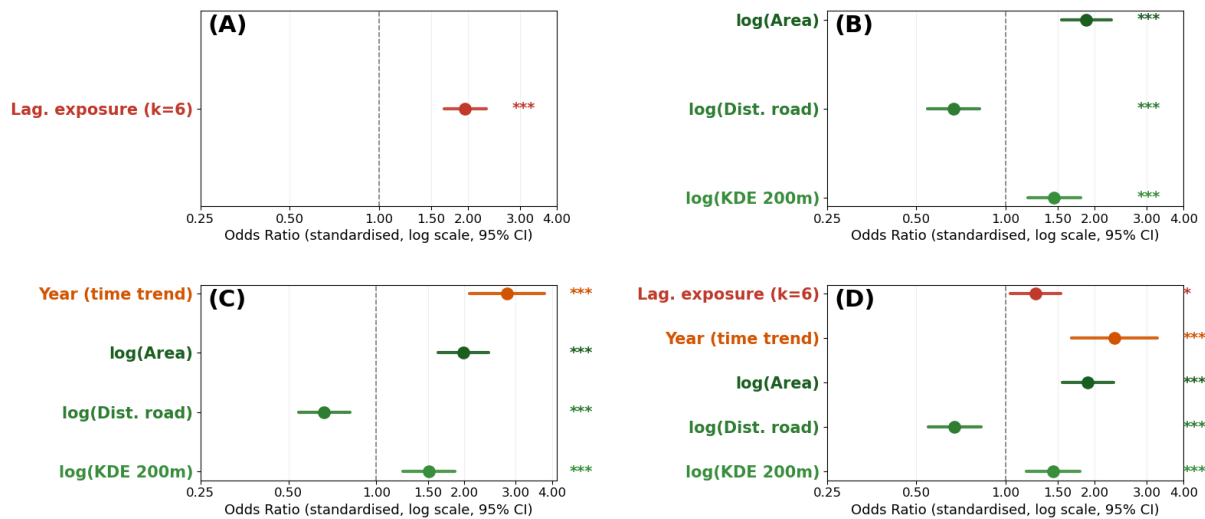


Figure 37: Standardised odds ratios (OR) with 95% confidence intervals for four progressive model specifications. (A) lagged neighbourhood exposure only, (B) spatial predictors only, (C) year trend and physical predictors, (D) full spatio-temporal model including exposure, year trend, and spatial predictors. All predictors were standardised prior to modelling; ORs reflect the effect of a one standard deviation increase. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, ns = not significant.

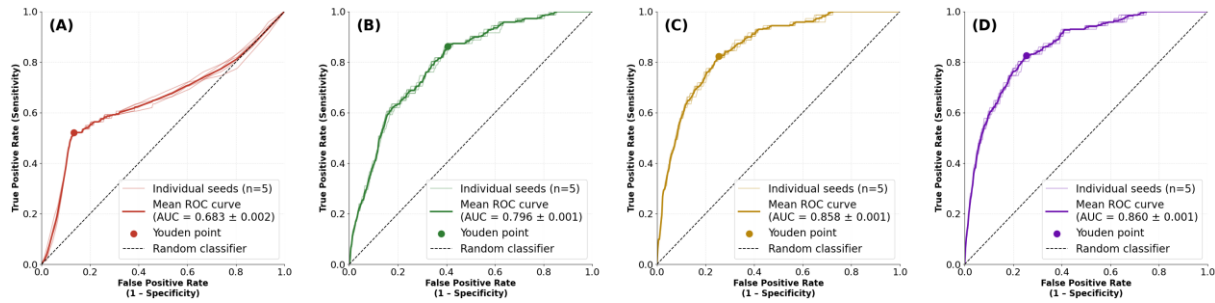


Figure 38: Cross-validated ROC curves (10-fold, 5 seeds) for four progressive discrete-time hazard model specifications. (A) lagged neighbourhood exposure only, (B) spatial predictors only, (C) year trend and physical predictors, (D) full spatio-temporal model including exposure, year trend, and spatial predictors

Model A, containing only the exposure variable, confirms a strong raw association between neighbourhood exposure and adoption (standardised OR = 1.96, $p < 0.001$, cross-validated AUC = 0.683 ± 0.002). This establishes the raw association before accounting for any physical or temporal variables.

Model B, containing only the three spatial predictors, refitted on the hazard panel, confirmed that total area, distance to nearest road and KDE settlement pressure remain significant predictors of adoption timing. No problematic multicollinearity was detected (maximum VIF = 1.07). Model B yielded a cross-validated AUC of 0.796 ± 0.001 and AIC of 912.9. This AUC differs slightly from that of the static spatial model (0.802 ± 0.005 , Section 3.3.1) due to the different modelling framework and dataset structure (gully-year panel, D4) and the removal of 64 gullies without known implementation age.

Adding Year to the physical model (Model C) produced a substantial improvement in model fit (AIC = 856.9, cross-validated AUC = 0.858 ± 0.001). The variable Year itself is strongly significant (OR = 2.80, $p = 1.25e-11$), indicating that GI adoption becomes substantially more likely in later years. The odds ratios of the three spatial predictors remained virtually unchanged compared to Model B. No problematic multicollinearity was detected in Model C (maximum VIF = 1.07).

The full spatio-temporal model (Model D), adding exposure to Model C, further reduced AIC and slightly improves AUC (AIC = 853.5, cross-validated AUC = 0.860 ± 0.001). This indicates that exposure has predictive power in addition to the temporal trend and spatial characteristics already considered. The standardised exposure OR (1.26) in Model D is significant at $p < 0.05$ but not at a more stricter $p < 0.001$ level. Again, no problematic multicollinearity was detected in Model D (maximum VIF = 1.30).

Table 18: Standardised odds ratios, 95% CI, p-values and VIF for models A, B, C and D. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, ns=not significant.

Variable	OR	95% CI	p-value	Significance	VIF
<i>Model A: Only exposure</i>					
Lag. exposure (k=6)	1.958	[1.660 - 2.310]	1.64e-15	***	1.00
<i>Model B: Only Physical variables</i>					
log(Area)	1.878	[1.546 - 2.281]	2.19e-10	***	1.01
log(Dist. road)	0.667	[0.544 - 0.817]	9.18e-05	***	1.06
log(KDE 200m)	1.46	[1.190 - 1.792]	2.84e-04	***	1.07
<i>Model C: Year and physical variables</i>					
Year (time trend)	2.797	[2.077 - 3.767]	1.25e-11	***	1.00
log(Area)	1.981	[1.624 - 2.417]	1.58e-11	***	1.01
log(Dist. road)	0.663	[0.543 - 0.810]	5.83e-05	***	1.06
log(KDE 200m)	1.509	[1.229 - 1.853]	8.62e-05	***	1.07
<i>Model D: Exposure, Year and Physical variables</i>					
Lag. exposure (k=6)	1.263	[1.037 - 1.539]	2.03e-02	*	1.30
Year (time trend)	2.338	[1.673 - 3.268]	6.52e-07	***	1.24
log(Area)	1.898	[1.554 - 2.319]	3.35e-10	***	1.02
log(Dist. road)	0.673	[0.549 - 0.826]	1.45e-04	***	1.07
log(KDE 200m)	1.449	[1.177 - 1.785]	4.82e-04	***	1.09

Table 19: Discrete-time hazard model statistics compared for model A, B, C and D. All datasets have 27,402 rows and 71 event rows.

	Model A: exposure only	Model B: Spatial variables	Model C: Year and spatial variables	Model D: Exposure, year and spatial variables
Pseudo-R ²	0.0579	0.0836	0.1424	0.1479
AIC	934.3	912.9	856.9	853.5
AUC (10-fold CV)	0.683 ± 0.002	0.796 ± 0.001	0.858 ± 0.001	0.860 ± 0.001

As established in Section 2.3.4, exposure remains significant after controlling for the temporal trend alone (OR=1.58, 95% CI [1.30–1.91], $p=2.65e-06$), while Year itself is also significant (OR=1.86, $p=1.58e-04$), confirming that both effects contribute independently. The attenuation observed in Model D, where the exposure OR drops from 1.58 to 1.26 upon adding spatial variables, suggests that part of the apparent exposure signal reflects spatial clustering of gullies with favourable physical characteristics rather than genuine neighbourhood exposure. Nevertheless, the exposure effect remains significant in Model D ($p=0.020$), indicating that a week local diffusion effect cannot be excluded.

CHAPTER 4

DISCUSSION

This discussion builds on the observed patterns of GI adoption in the Shafe catchment to interpret what drives variability in farmer responses to gully erosion. In four steps, the different research questions are addressed. After this, the limitations and avenues for future research are discussed.

4.1 Characteristics of mapped gullies and their interventions

4.1.1 Spatial distribution of gully interventions

Farmers in the Shafe catchment have responded to gully erosion through a diverse set of GIs. 18% of the mapped gullies in the spatial dataset contained at least one GI (D1, UAV-surveyed study area; Figure 18, Section 3.1), compared to 48.1% of gullies reported in the household survey (D2, Figure 21, Section 3.2).

This discrepancy primarily results from the two datasets reflecting different units of observation: the spatial dataset captures whether at least one GI is objectively present in a gully as a whole, while the household survey reflects individual farmer perspectives. Therefore, a single gully bordered by multiple farmers will appear once in D1 but may be reported as treated by each of those farmers independently in D2. Additionally, field observations and UAV-based detection inevitably missed a substantial share of GIs: only banana plantations were reliably identifiable in UAV imagery, meaning check dams and other interventions, especially smaller ones, could be systematically under detected in D1. Furthermore, the household survey asked about GIs ever applied, including those that may have failed or fully rehabilitated the gully, therefore no longer visible in the field. Farmers may also have reported on GIs implemented on land outside of the UAV-surveyed area. Moreover, a large fraction of the gullies in the spatial dataset are located in degraded rangeland (such as in Layo Terga Case 7, Figure 8, Section 2.2.1), while farmers may not consider these lands a part of their managed land, and may thus not report on them. Lastly, self-reported adoption rates may be overestimated, as farmers may tend to present their land management in a socially desirable way (Grimm, 2010).

Despite this discrepancy, the spatial distribution of treated gullies shows a consistent pattern: GI adoption is significantly clustered rather than randomly distributed (Moran's I, Section 3.4.1), yet clusters occur throughout the full surveyed area rather than being confined to a single zone.

Banana plantations dominate across all cases, while check dams and trees show a more spatially concentrated distribution (Figure 19A, Section 3.1.1).

4.1.2 Dominant gully intervention types and their relationship

In both datasets, different GIs types are implemented throughout the study area. Combinations of check dams and vegetation (including banana, other crops or grasses) are frequently observed in both D1 (25% combination) and D2 (51.4% combination) (Figures 19B and 21, Sections 3.1.1 and 3.1.2).

Banana plantation is the dominant intervention, present in 73.9% of all mapped grouped GIs (D1). This is confirmed by the household surveys, where banana plantations similarly represent the most frequently reported farming intervention (43%, D2). Given the economic importance of banana cultivation in this region (Bekeko et al., 2025), this reflects a clear farmer preference for economically valuable species as GIs, consistent with findings on species selection in the broader literature (Reubens, 2010; Talema et al., 2017). Additionally, banana requires less labour input than check dam construction, making it more accessible for households with fewer available family members. While banana root systems may contribute to soil stabilisation, their effectiveness for erosion control is less well-documented than for other plant species recommended (Reubens, 2010; Talema et al., 2017).

The agronomic rationale for combining banana with check dams becomes clear when considering the physical process of gully infilling. By implementing check dams, sediment deposition converts the gully floor from a V-shape to successive nearly horizontal steps (Nyssen et al., 2004). Taken together with the higher soil moisture found on the gully floor compared to adjacent cropland (Mekonnen et al., 2026), this implies that banana cultivation inside the gully, combined with check dam implementation, is both an economically motivated and agronomically rational choice. Figure 39 demonstrates infilling of a check dam.

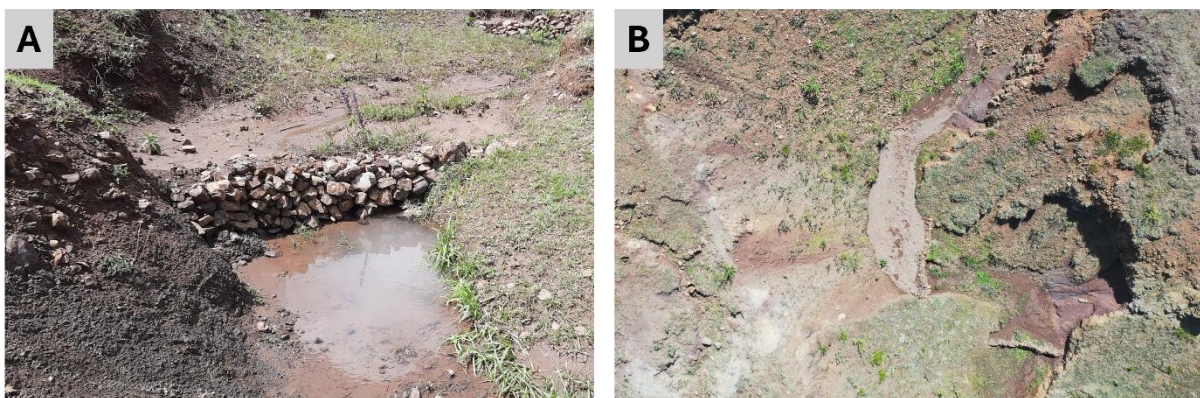


Figure 39: (A) Loose rock check dam with sediment accumulated upstream. (B) Aerial view of two check dams with sediment infilling between consecutive dams (light-grey deposits). Photos: Y. Mekonnen, [July 2024].

However, this agronomic potential comes with an important nuance. Soil samples taken behind old and new check dams during fieldwork in September 2025, preliminarily analysed by co-supervisor Y. Mekonnen but falling outside of the scope of this study, suggest that older check dams (± 30 years) show considerably deeper and more nutrient-rich soils than newer ones. As check dams fill up with fresh and coarse material, they may contain fewer nutrients initially, which are nonetheless critical for cultivatable land. This may explain why banana, a relatively robust crop, is preferred over more nutrient-demanding staple crops such as false banana (*Enset*). However, the exact productivity of filled-in check dam sediments and their suitability for different crop types remains poorly understood at catchment scale, as the preliminary soil samples collected in this study cover only a limited number of check dams within the same gully system.

Economic benefit is rarely cited as a primary motivation to implement GIs (23.8% for farming interventions, 11.1% for physical measures), yet emerges more prominently as a reported positive impact (53.4% for farming interventions, 22.1% for physical) (Section 3.2.2). The dominance of banana, a cash crop, confirms that economic motivations may be more important than explicitly reported by farmers. Moreover, poor soil condition is the most cited challenge for physical measures (70.3%), despite check dams being structural rather than agronomic in nature, suggesting farmers may perceive check dams as foundations for subsequent crop establishment.

Together, this suggests that farmers simultaneously stabilise the gully and use the gully floor as a complementary farming space, reflecting the concept of converting degraded land into productive use (Mekuria et al., 2024). However, this economic motivation may be underreported in the household survey, as farmers potentially tend to present their decisions in socially desirable terms (Grimm, 2010), in this context taking care of one's land, rather than acknowledging personal (economic) gain.

Check dams remain an essential GI, despite their technical implementation posing a real barrier. Farmers report considerably more challenges with physical measures (mean 2.9 challenges per gully) than with farming or grass interventions (~ 1.8 challenge per gully) (Figure 28B, Section 3.2.2), consistent with documented check dam failure rates (Frankl et al., 2021; Nyssen et al., 2004). These reported challenges include lack of resources, technical support, regular maintenance, and inadequate design. This is illustrated by the AMU-IUC demonstration workshop of August 2025 in Layo Terga Case 1, attended by the author, in which farmers were guided in check dam construction by local experts (Figure 40), with particular emphasis on correct spillway construction and dam spacing, both critical for structural longevity (Nyssen et al., 2004).



Figure 40: AMU-IUC demonstration workshop on gully check dam construction, Layo Terga Case 1, August 2025. (A) Farmers collaboratively transporting stones to the gully, (B) check dam construction under expert guidance. Photos by author, [August 2025].

4.2 Factors influencing gully interventions

The factors shaping GI adoption were investigated by examining relationships between the spatial dataset (D1) and the socio-economic dataset (D2). The latter captures not only objective farmer and plot characteristics, but also farmers' perceptual assessments of their gullies (e.g. perceived impact severity and plot productivity).

4.2.1 Gully characteristics

Treated gullies are significantly larger than untreated ones in terms of area, length, width, and elevation difference (Figure 22, Section 3.2.1), with gully area emerging as the strongest independent predictor (OR=2.44 in spatial model, Section 3.3.1). Length, width, and elevation difference do not retain significance due to multicollinearity, suggesting area serves as an adequate composite proxy. Area captures both the primarily ongoing widening process (Belayneh et al., 2022; Mekonnen et al., 2026) and the length already accumulated. However, as D1 examines adoption at the gully level as a whole, this effect should be interpreted with caution: larger gullies involve more farmers, mechanically increasing the probability that at least one GI is present, independent of individual farmer responses to erosion severity.

Slope, identified as a driver of gully initiation (Vanmaercke et al., 2021), shows no significant association with GI adoption. However, steeper slopes may reduce the feasibility of check dam construction by increasing structural failure rates (Frankl et al., 2021), thereby counteracting any erosion-driven urgency to act. Several other physical drivers, including rainfall intensity, contributing area and soil characteristics (Vanmaercke et al., 2016, 2021), were not directly assessed, as the analysis focused on observable gully morphology. These factors are nonetheless assumed to be partly reflected in the assessed characteristics (e.g. gully area), which integrates their cumulative effect on gully development over time. Elevation, explored as an indirect proxy for rainfall variability and agro-ecological conditions, showed no significant

association. This could be due to the insufficient elevation range within this relatively small catchment, an inadequate proxy relationship, or the overruling influence of other factors.

Gully-level variables from the household survey (D2) reveal additional patterns that both complement and complicate the spatial findings. A key interaction exists between gully size (D1) and ownership (D2): larger gullies are more likely to cross multiple plot boundaries and thus be shared between farmers. Yet, gullies shared between multiple farmers are less likely to be treated by any individual farmer (OR=1.71 in socio-economic model, Section 3.3.2). This likely reflects multiple mechanisms, though these remain poorly understood. The following should therefore be considered as preliminary hypotheses for future research.

First, farmers located downstream may face higher runoff energy, making intervention feel less feasible. Upstream GI implementation could moreover reduce runoff energy for downstream farmers, potentially facilitating further adoption in a downstream direction. Second, plot boundaries are often oriented perpendicular to the gully, leaving individual farmers with only a narrow stretch of gully floor, potentially too small to justify check dam construction. Additionally, when plots border opposite sides of the gully, ownership of the thalweg itself may be ambiguous, further complicating intervention decisions.

The vast majority of gullies are perceived as having moderate to very severe impact, reflecting the critical erosion situation in the study area. This perceived impact score (D2) presents a further nuance with gully size (D1): adoption rates are highest for moderate to severe impact gullies, while very severely affected gullies show a comparatively lower treatment rate (Figure 26C, Section 3.2.2). Although this association did not retain significance in the multivariate model, it is conceptually important as it suggests a non-linear relationship: below a certain threshold, approximately “severely affected”, greater perceived severity stimulates adoption, consistent with literature (Ervin & Ervin, 1982; Tesfaye et al., 2014b). Beyond this threshold, however, gullies may be perceived as too severe to rehabilitate, reducing motivation to act. This is consistent with Ayele et al. (2015), who found that farmers initially refused rehabilitation because they considered it impossible. A negative association between perceived severity and general SWCM adoption was also reported by Yirgu (2022), though this relation was attributed to land requirements of conservation structures rather than perceived infeasibility. The underlying mechanisms may therefore differ between general SWCM and gully-specific interventions. Further research targeting this non-linear relationship would be valuable.

Gully age shows a marginally significant association with GI adoption (Table 10, Section 3.2.2), with younger gullies more likely to be treated, suggesting farmers respond with greater urgency when erosion is still accelerating (Vanmaercke et al., 2016). However, on the same level, gully

activity shows no significant association with adoption. If urgency were the main driver, active gullies would be expected to show higher treatment rates. Assessing real (D1), rather than perceived gully activity (D2), was impossible within the scope of this study, but could yield valuable additional insights into this age-activity discrepancy.

While the difference between the two datasets should be taken into account, the findings point to a complex relationship between gully characteristics and GI adoption. Hypothesis 1 (Section 1.4), which predicted that more severe gully erosion leads to higher GI adoption, is only partially supported. Rather, a non-linear relationship is suggested where gully impact may stimulate adoption up to a certain threshold, whereafter it may discourage it. A key finding beyond this hypothesis concerns the role of gully ownership, a dynamic not anticipated based on literature but clearly relevant. As its exact role remains poorly understood, the mechanisms hypothesized above warrant future research.

4.2.2 The role of spatial proximity

In terms of spatial proximity, distance to the nearest road (D1, OR = 0.67 in spatial model) and built-up area density (D1, OR = 1.78 in spatial model) show highly significant associations with GI adoption (Section 3.3.1). This likely reflects a combination of interrelated mechanisms.

Road access facilitates material transport for check dam construction. This may explain why road distance is significant in this study but not in studies of general SWCM adoption (Teshome et al., 2016), where material transport may be less intensive. In contrast, distance to the river, from which stones are typically sourced (according to farmer during informal conversations), shows no significant association with GI adoption. However, given the dominance of banana plantations in the study area, which require little material transport, river proximity may simply be less relevant overall.

Proximity is directly related to travel time to plots, emerging as a dominant factor in D2 (OR=0.60 in socio-economic model, Section 3.3.2), consistent with the above D1 findings. Farmer rankings confirm this pattern, with homestead proximity rated as the second most important land characteristic overall (Figure 29, Section 3.2.2). Land fragmentation in the Gamo district further increases travel time between plots (Cholo et al., 2019), reducing the time and energy available for labour-intensive interventions (Nigussie et al., 2017).

Beyond individual plot accessibility, the significance of settlement pressure (D1) may reflect an additional mechanism. Although household size shows no significant association with GI adoption (D2), informal collective labour networks are well-established in the study area (Section 1.3.5), extending the effective labour pool beyond the individual household. Higher

settlement density may therefore partly capture the availability of collective labour for intervention. This is consistent with the broader observation that higher population density has been linked to more active land management (Nyssen et al., 2009).

Taken together, spatial proximity in D1, travel rank in D2, and farmer self-reported rankings provide consistent evidence across three independent sources that accessibility is a key determinant of GI adoption. H2 is therefore supported, with the non-significance of river distance representing a partial exception.

4.2.3 Adjacent plot characteristics

Proximity to the homestead has an additional implication beyond travel time alone: plots closer to the homestead tend to receive more management attention and are generally more productive (Assefa et al., 2020), a pattern partially reflected in this dataset ($\rho = -0.36$ between travel rank and log plot yield; Appendix Figure C1). Both perceived plot productivity and plot yield are significant predictors of GI adoption in D2 (Section 3.2.2), further confirmed by farmer rankings where productivity ranks as the most important land characteristic (Figure 29, Section 3.2.2).

The number of gullies per plot reinforces this productivity argument, showing a significant negative association with GI adoption (OR = 0.67 in socio-economic model, Section 3.3.2). Plots with more gullies experience greater cumulative productivity loss and are more likely to be perceived as less worth investing in. Moreover, farmers may even underestimate this productivity loss. Mekonnen et al. (2026) show that gully erosion reduces yields not only through direct land loss but also through soil moisture depletion in adjacent fields, an effect that may go unnoticed until it becomes severe. This may create a vicious cycle: severely affected plots gradually shift to rangeland, further reducing the incentive to intervene and allowing gully expansion to continue unchecked (Mekonnen et al., 2026). However, whether the specific land use type directly mediates GI adoption could not be assessed due to the absence of a reliable land use map. This represents an important avenue for future research.

One farmer in the dataset captures this compounding effect of distance and productivity in a single response. He manages three plots, with his only gully in the most distant plot (1.5 hours travel versus 4 and 20 minutes). In the survey remarks, he explicitly stated: "The plot is too far and also not productive, so not interested to implement anything".

In contrast, the weighted N-content variable, used as a proxy for soil fertility in D1, shows no significant association. However, this likely reflects both the spatial uncertainty inherent to SoilGrids data at this local scale (Poggio et al., 2021) and a more fundamental conceptual

limitation: farmers' perception of plot productivity integrates multiple interacting factors beyond soil nutrients alone. This may explain why the perceived plot productivity and self-reported yield (D2) are stronger predictors than a single objective soil characteristic.

Lastly, land tenure security has been identified as a significant driver of general SWCM adoption (Teshome et al., 2016; Daba, 2003; Adere et al., 2022). In contrast to the broader Ethiopian context where many farmers lack official tenure documentation (Talema et al., 2017), 96.1% of plots in this study are stated to be owner-certified, leaving insufficient variation to detect a plot-level tenure effect.

Overall, the findings support H3 since perceived plot productivity is found to be a key driver of GI adoption at plot level. Given that land use type is likely correlated with both spatial proximity and plot productivity, it may represent an additional and underexplored driver of GI adoption. Plots with active gullies may already have shifted to rangeland, reducing intervention likelihood independently of proximity or productivity perceptions. Directly investigating the role of land use type therefore represents an important avenue for future research. H3 further hypothesised that secure plot ownership correlates with GI adoption. While tenure status' role could not be assessed due to insufficient variation in the data, sole gully ownership was found to significantly increase intervention likelihood.

4.2.4 Farmer profile for gully interventions

Near-universal willingness to adopt GI is evidenced by multiple sources: 88.2% of farmers in our dataset implemented at least one GI, and 98.9% expressed serious concern about gully erosion (Mekonnen et al., 2026). Among non-adopters, only 14% indicated no interest implementing GIs in the future, with the remainder non-adopting farmers expressing interest in the same intervention types as current adopters (Figure 30A, Section 3.2.2). Yet motivation alone does not translate into action. Bewket (2007) found that 98.4% of Ethiopian farmers recognised SWC technologies as effective, yet the majority lacked intention to maintain them after external support ended, primarily due to labour and resource constraints.

This near-universal adoption at farmer level combined with the much lower gully-level treatment rate (18% in D1, 48% in D2) suggests that the key question is not whether farmers adopt GIs, but where they choose to do so. Farmers whose (part of the) gullies appear untreated in D1, in most cases report in D2 to have implemented GIs elsewhere on their land.

At the farmer level (D2), no variable shows a significant association with GI adoption rate. When farmer characteristics are examined at the gully level (duplication of farmer-level characteristics per gully), however, several variables show significant Spearman correlations,

of which only household economic surplus is retained in the model (OR=1.33 in socio-economic model). The non-significance of annual income and expenses suggests that available financial surplus, rather than total income, enables GI implementation. This is consistent with evidence that access to financial resources is a determinant of conservation adoption (Tesfaye et al., 2014b).

This is further supported by farmer rankings of factors influencing GI adoption (Figure 29, Section 3.2.2). At the broad category level, financial and material factors are ranked first or second by over 65% of farmers (Figure 29A). However, within this category, manpower and materials rank most important while direct financial support ranks least important (Figure 29B). This could suggest that surplus functions primarily as a means to mobilise labour and materials rather than as a direct investment. This is also reflected in SWCM literature, where labour availability is a strong predictor of adoption (Bewket, 2007; Teshome et al., 2016). This is confirmed by farmer responses in the open questions, where labour and material constraints are the most frequently cited barriers, and illustrated by one farmer who stated: "If I have labour and budget, I decided to conserve my plot by *debo* or community group". Such collective labour arrangements may therefore reduce this burden, particularly for labour-intensive check dam construction.

Beyond its material function, surplus may reflect a broader psychological dynamic. Haushofer & Fehr (2014) argue that poverty causes chronic stress, which in turn favours short-term thinking and risk aversion. This could thus potentially reduce investment in long-term interventions, independently of material constraints. The significance of surplus in the model may therefore partly capture this psychological pathway rather than material capacity alone.

The weakness of farmer-level predictors partly reflects the homogeneity of the study population: most farmers are subsistence-oriented, have limited formal education, and highly depend on agriculture, leaving insufficient variation to detect strong individual-level effects. This does not mean socio-economic factors are unimportant, rather, their effect may only become apparent when comparing more diverse populations. However, one variable showing sufficient differentiation is whether farming is a farmer's sole income strategy: farmers depending exclusively on agriculture are more likely to implement GIs (Table 14, section 3.3.2), consistent with evidence that off-farm engagement reduces both time and motivation for labour-intensive interventions (Ervin & Ervin, 1982; Tesfaye et al., 2014a). However, this association did not retain significance in the multivariate model.

Taken together, the farmer-level analysis suggests that willingness for GI adoption is almost universal: most farmers in the study area would implement GIs if they could, as consistently

expressed in the open survey responses. Within this group, those with the least economic surplus may face additional barriers, whether material, psychological, or both. GI adoption is thus driven by necessity and available capacity rather than socio-economic advantage. H4 is therefore largely supported: farmers with sufficient economic surplus and greater dependence on agriculture as their primary livelihood are more likely to implement GIs, while off-farm engagement reduces this likelihood. The role of livestock ownership was not assessed, as its complexity (i.e. shared ownership and diverse livestock types) exceeded the scope of this study.

4.3 Static predictive modelling of gully intervention priority

Part of this study examines whether gully intervention likelihood can be predicted from spatial and socio-economic characteristics. Two complementary models were developed with distinct purposes: the spatial model (D1) is designed to be geographically transferable, identifying which gullies across the landscape are most likely to be prioritised for treatment based on observable physical characteristics. The socio-economic model (D2) is explanatory and policy-relevant, identifying which farmer and plot characteristics enable or constrain GI adoption, thereby informing targeted support strategies. Logistic regression was chosen as the modelling approach due to its interpretability, providing a direct linkage between predictor variables and predicted outcomes (Assis et al., 2025)

Based on only three physical variables, gully area, road distance, and settlement pressure proximity, the spatial model achieves an AUC of 0.80, demonstrating that fairly robust spatial predictions are feasible. Predicted probabilities are used as a relative ranking of treatment likelihood rather than absolute estimates due to data imbalance (18% treated) (Wilson et al., 2005), meaning the primary question is not whether a gully will be treated, but which gullies are comparatively more likely to be prioritised. However, as discussed in Section 4.2.1, gully area functions as an umbrella variable that may inflate predicted probabilities for large shared gullies, as the probability of at least one GI adoption will evidently be higher if more farmers boarder the gully.

The socio-economic model (D2) achieves a lower AUC of 0.719, reflecting the inherently complex nature of individual adoption decisions. The retained variables collectively sketch a profile of gullies most likely to be treated. These are those owned by a single farmer, located in productive and accessible plots, and managed by farmers with available economic surplus. This profile suggests that policy interventions could most effectively target accessible, productive plots where individual ownership creates clear incentives. While shared gullies may

require dedicated collective action support, they should not be overlooked: their larger size means they score high in the spatial model, reflecting the greater likelihood that at least one of the bordering farmers will intervene. Future incorporation of land use data could further improve model performance, given the likely role of rangeland conversion discussed in Section 4.2.3.

The mixed model offered no added value over the spatial model, primarily due to the small linked dataset ($n = 242$). This challenge is likely to persist in future studies given the extreme land fragmentation in the study area, and represents an important methodological consideration for similar contexts.

4.4 Towards a diffusion model of gully intervention adoption

Moran's I analysis confirms that gullies with GIs are significantly clustered in space (Section 3.4.1), consistent with the theoretical expectation that adoption clusters emerge when neighbours influence each other's decisions (Valente, 2005). The central question is whether these clusters reflect an endogenous effect (farmers adopting because neighbours adopted), an exogenous effect arising from shared favourable physical conditions (e.g. proximity to roads), or a correlated effect driven by unmeasured contextual factors (e.g. cultural norms, community arrangements) (Manski, 1993). A complementary Moran's I analysis of GI implementation dates (Section 3.4.2) showed no significant temporal clustering, yet observed Moran's I values consistently exceeded the simulated mean and several configurations bordered significance. This limited signal is likely a conservative estimate: 64 of the 135 treated gullies lack a known implementation date, therefore, gullies appearing spatially isolated may in fact lie adjacent to earlier but undated GIs. Together, the confirmed spatial clustering and the suggestive temporal signal motivate a more formal test for diffusion.

To formally test for this, a discrete-time hazard model was fitted on D4 (687 gullies, 71 adoption events; Section 3.4.3). Group 2 gullies ($n=64$) were excluded from model fitting due to their unknown implementation date, but retained for exposure calculation through a probabilistic CDF approach. The key underlying assumption was that Group 2 gullies follow the same temporal adoption trend as Group 1. This assumption is validated by comparing the Group 1 CDF against an independently constructed CDF from D2, which captures a broader spatial extent. The close visual agreement between both curves (Figure 41) confirms this, and furthermore suggests that the UAV-surveyed area is broadly representative of wider adoption dynamics.

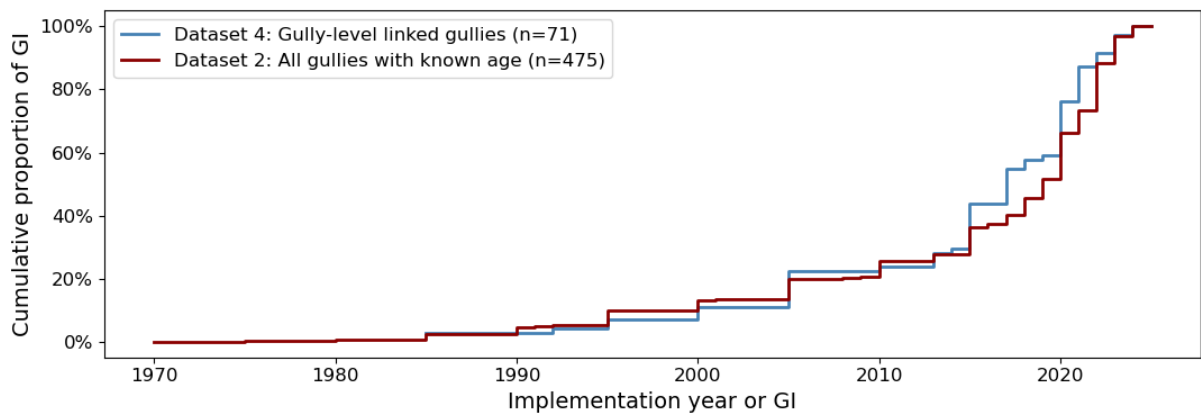


Figure 41: Cumulative distribution function of the 71 D4 linked spatial and socio-economic gullies (blue) and the 475 socio-economic gullies in D2 (brown).

Before interpreting the model results, the CDF shape itself provides important context. Diffusion processes theoretically produce a S-shaped curve, where acceleration plateaus as the adopter pool becomes saturated (Amati et al., 2019). The exponential pattern observed here (without plateau) could suggest that the study area is in an early-to-mid adoption phase, consistent with the near-universal adoption willingness reported in Section 4.2.4. Both CDFs moreover show a marked acceleration after approximately 2015, suggesting GI adoption has intensified substantially in recent years.

The progressive model specifications (Section 3.4.3, Figure 37), each adding an additional control, disentangle three effect types. The raw exposure signal (Model A, OR = 1.96) is inflated by two independent confounders: spatial clustering of physically favourable gullies, and the mechanical rise of exposure scores over time as more neighbours adopt catchment-wide. Model D controls for both simultaneously. Exposure remains significant after these controls (OR=1.26, $p=0.020$), indicating a residual endogenous signal beyond what physical conditions and the general temporal trend alone explain. The attenuation from Model A to Model D confirms that both confounders have a real effect, yet, a marginally significant exposure residue remains.

This residual could however be interpreted as a likely underestimate of the true diffusion signal, due to several constraints. First, the implementation timing of 64 gullies without specified age is unknown and must be estimated from the CDF curve, an assumption validated above, but inherently uncertain. Second, using only the oldest measure per gully misses intra-gully diffusion dynamics. This is proven by the Morans I analysis of clusters in time, where a stronger signal was observed at measure (point) level, than at gully (polygon) level (Section 3.4.2). Third, the model operates at gully level, while diffusion in practice occurs between farmers through social networks that geographic proximity only partially captures (Abdulai et al., 2021; Genius et al., 2014). Furthermore, given extreme land fragmentation, a farmer may learn from

a neighbouring farmer yet choose to intervene on an entirely different plot based on his own priorities

Complementary evidence from D2 points in the same direction. While farmers overwhelmingly report their own decision as their primary source of influence (84–95%, Figure 27B, Section 3.2.2), multiple reasons are commonly cited alongside this. Among these secondary influences, formal institutional support ranks ahead of neighbourhood influence, though both are mentioned by a meaningful share of farmers. This likely still underestimates the true peer effect: again, social desirability may lead farmers to frame decisions as self-motivated (Grimm, 2010) or question misinterpretation may occur (Stern et al., 2014). Qualitative evidence supports this: a pioneer farmer reported during the interview that "he had no support and knowledge to do the measures, as he was the first one to do it here", suggesting that later adopters may benefit from informally diffused knowledge without recognising it as such. Farmers who attended the AMU-IUC workshop similarly informally cited the pioneer farmer as a key knowledge source, yet still ranked neighbourhood influence last in their survey answers. Furthermore, peer influence may go unrecognised precisely because most people prefer to wait until others have tried an innovation first (Valente, 1996). This tendency is likely amplified by the risk-averse attitude that poverty generally induces, making farmers hesitant to commit scarce resources (Haushofer & Fehr, 2014), as discussed in Section 4.2.4.

Overall, H5 is partially supported: a weak but detectable endogenous diffusion signal is present in the spatial dataset, likely underestimated by methodological constraints. Additional insights from household interviews strengthen this argument. However, a potential unobservable correlated effect, the third factor according to Manski (1993), cannot be formally tested and therefore remains a potential alternative explanation that cannot be excluded. A definitive causal claim cannot be made, but this study provides, to our knowledge, the first application of a discrete-time hazard model to gully intervention adoption. Therefore, it is a methodological foundation for future research, particularly if Group 2 (gullies without known age) implementation dates could be established.

A stricter normalisation removing the temporal trend from the exposure variable itself was explored (Appendix E2-3), but produced inconclusive results (OR=1.07, $p=0.23$) due to its own limitations (e.g. numerical instability in early years, non-linear peer influence dynamics). It therefore neither confirms nor contradicts the signal in Model D. This ambiguity highlights that neighbourhood exposure measurement warrants further refinement before stronger conclusions can be drawn, with the most meaningful improvement coming from determining Group 2 implementation dates directly.

4.5 Limitations of the study and future recommendations

Several limitations have been noted throughout this discussion, the most important are summarised here.

The spatial dataset (D1) likely underestimates GI prevalence, as complete field coverage could not always be guaranteed due to accessibility constraints, and only banana plantations were reliably identifiable in UAV imagery, illustrated by the large D1-D2 discrepancy in check dam prevalence (Section 4.1.1). The household survey (D2) is likely subject to well-documented survey errors including social desirability bias (Grimm, 2010), measurement error, and interviewer effects (Stern et al., 2014). This is presumably amplified by the communication process from researchers to enumerators to farmers, with additional translation noise between Amharic and the local Gamo language. Most importantly, improving the spatial linkage between D1 and D2 remains the key priority for future research.

This study examined GI adoption in general, without distinguishing between intervention types. Given the clear differences between banana cultivation and check dam construction in terms of labour requirements, economic motivations, and physical effectiveness, future research could therefore benefit from distinguishing between intervention types when modelling GI adoption, provided the dataset is large enough to support such disaggregation.

Several predictor variables fell beyond the scope of this study. Well-documented drivers of gully erosion such as upslope contributing area or rainfall intensity (Vanmaercke et al., 2021), were not directly assessed, but were assumed to be partly reflected in gully morphology (Section 4.2.1). Soil fertility proxies and gully activity status could similarly be refined. Importantly, gully widening rates, the dominant erosion process in this area (Belayneh et al., 2022; Mekonnen et al., 2026), could be incorporated by comparing with earlier imagery (i.e. Belayneh et al., 2022). Land use type could not be assessed due to the absence of a reliable land use map, but could potentially reinforce the productivity-accessibility argument developed in Section 4.2.3. Finally, livestock ownership was identified in the literature as a potential predictor (Section 1.3.4) but could not be meaningfully integrated due to the complex data structure and ownership arrangements in the study area.

Several conceptual questions warrant dedicated future research. The role of gully area as the dominant predictor deserves further investigation, specifically disentangling erosion severity from the mechanical effect of more farmers bordering larger gullies. The non-linear relationship between perceived gully severity and adoption likelihood, and the actual productivity of gully-

based farming as an economic incentive, similarly represent underexplored questions with direct practical relevance.

Shared gully ownership emerged as a key but poorly understood factor, for which preliminary hypotheses were proposed in Section 4.2.1, including how ownership is exactly divided between farmers, and whether upstream GI implementation influences downstream adoption decisions. Additionally, future research could link this ownership dynamic to the diffusion analysis in Section 4.4, investigating whether GI implementation by one farmer within a gully influences adoption by neighbouring farmers within the same gully.

Finally, multiple complementary lines of evidence collectively suggest that a spatial diffusion process may be currently active in the Shafe catchment (Section 4.4). Despite the substantial data limitations outlined above, the convergence of these independent signals provides a first cautious indication that neighbourhood exposure genuinely influences GI adoption timing. Confirming this would require implementation dates for all treated gullies, analysis at the individual GI level rather than the oldest intervention per gully, and incorporation of social network data beyond geographic proximity alone.

CHAPTER 5

CONCLUSION

Gully intervention adoption in the Shafe catchment is not uniformly distributed. While farmers show near-universal willingness to act, where they choose to intervene is shaped by a consistent set of spatial, socio-economic and perceptual factors. Four research questions addressed this overarching pattern, with study findings resulting in scientific insights and practical implications.

RQ1 asks what GIs have been implemented by farmers to reverse gully-induced problems, and how these interventions are distributed spatially. Field and drone observations identified at least one intervention in 18% of mapped gullies across the drone-surveyed area. The household survey, which captures individual farmer decisions across all their gullies (many of which are shared with neighbouring farmers), suggests 48% of reported gullies have been treated at some point, with 88% of surveyed farmers having implemented at least one GI somewhere on their land. The GIs in the Shafe catchment are dominated by banana plantations and check dam measures, frequently combined, and distributed in spatial clusters across the full surveyed area. The integrated check dam-banana strategy reflects both a genuine concern for land rehabilitation and economic preferences, with the gully floor serving as complementary farming space once stabilised through check dam construction. However, this pattern is likely more economically motivated than farmer self-reports suggest.

RQ2 addresses the physical, socio-economic and perceptual factors that explain why some gullies are treated, while others are left untouched. At the level of the mapped gully dataset, gullies with a larger area and greater proximity to roads and surrounding settlement pressure are more likely to contain at least one GI. From an individual farmer's perspective, this proximity is confirmed: gullies are preferentially treated when located on accessible plots close to the homestead, and on productive plots with higher yields and fewer competing gullies. These two factors likely reinforcing each other. The gully itself is most likely younger and owned exclusively by that specific farmer. Additionally, the gully is perceived as having a moderate to severe impact, as adoption likelihood declines for the most severely affected gullies that could be perceived as infeasible to rehabilitate. Across the study area, farmers share a broadly similar profile of subsistence-oriented smallholders with high dependence on agriculture. Within this homogeneous group, exclusive dependence on agriculture as the primary livelihood and sufficient economic surplus are associated with a higher likelihood of GI adoption. This surplus is probably used to mobilise the required labour and materials, but potentially also reflecting the risk-averse behaviour that poverty induces, making farmers with less surplus hesitant to invest in interventions that may fail.

RQ3 seeks to establish predictive models that identify which gullies are most likely to be prioritized for intervention. Our predictive models can identify these gullies to a reasonable but limited extent. Based on only three spatial variables, gully area, distance to roads, and surrounding settlement pressure, the spatial model achieves an AUC of 0.80. This provides a relative ranking of treatment likelihood across the landscape. However, gully area may partly inflate predictions for large shared gullies, as the probability of at least one farmer intervening increases mechanically with the number of farmers bordering a gully. The socio-economic model (AUC=0.719) identifies gullies most likely to be treated as those owned by a single farmer, located on accessible and productive (higher yield, lower amount of gullies) plots, managed by a farmer with sufficient economic surplus. Together, these complementary models provide a first step towards a practical targeting framework, though both carry uncertainties that limit direct application without further validation.

Finally, RQ4 asks to what extent GI adoption spreads as a diffusion process. GI adoption in the Shafe catchment is found to be significantly clustered in space. A discrete-time hazard model found that neighbourhood exposure is a significant predictor of GI adoption, even after accounting for spatial gully characteristics and the general temporal increase in adoption. This suggests that GIs may spread as a diffusion process through informal knowledge sharing between neighbouring farmers, consistent with what has been demonstrated for many other agricultural innovations. Farmer interviews point in the same direction, though neighbourhood influence is likely underreported due to social desirability. Nevertheless, the effect is weak, a correlated effect cannot be excluded, and substantial uncertainties remain.

These findings carry several practical implications, rooted in a bottom-up understanding of farmer behaviour. Farmers in the Shafe catchment already demonstrate a near-universal willingness to act against gully erosion, and the majority have implemented at least one GI. The challenge is therefore not to convince farmers to intervene, but to support them in doing so more effectively and in more locations. Given that gully erosion reduces household income by an estimated 13.8% on average (Mekonnen et al., 2026), the urgency of this support is clear.

Farmers combine gully stabilisation with productive land use, most notably through banana cultivation on the gully floor. Support programmes could reinforce this dual strategy by framing gully rehabilitation not purely in conservation terms, but as a complementary economic opportunity. Two key constraints consistently identified by farmers are manpower and material availability. Support efforts should therefore prioritise facilitating access to labour and materials, leveraging both the informal collective labour networks already present in the study area and formal demonstration workshops. Shared gullies require particular attention, as

collective action support is needed where individual ownership is ambiguous, though the mechanisms underlying this ownership effect remain poorly understood.

This study is, to our knowledge, the first to demonstrate indications of a spatial diffusion process for gully interventions. Further research building on complete implementation dates and explicit social network data is needed to confirm this. Nevertheless, this indication of diffusion suggests for support programmes (formal information spreading) to strategically target pioneer farmers across different locations in the catchment, as their visible success may trigger adoption among neighbouring farmers, leading to further informal information spreading.

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APPENDICES

Appendix A: Full overview of individual gully interventions

Table A1: 20Full overview of individual gully interventions identified through field observations (n=269) in the UAV-surveyed area.

Crops (n=194)	n	Trees (n=67)	n	Others	n
Banana	83	Eucalyptus	33	Stone check dams	49
Sugar Cane	16	Tid	18	Grasses	14
Sorghum	10	Ficus	7		
Haricot Bean	9	Wera	4		
Casava	7	Cortch	2		
Chat	5	Cordia Africana	2		
Sweet patato	2	Bisana	1		
Soy bean	2				
Barley	2				
Maize	1				
Enset	1				
Berbera	1				

Table A2: Full overview of individual gully interventions identified through UAV-based remote sensing (n=60) in the UAV-surveyed area.

Crops (n=55)	n	Trees (n=70)	n	Others	n
Banana	53	Eucalyptus	3	Stone check dams	2
Other crops	2			Grasses	0

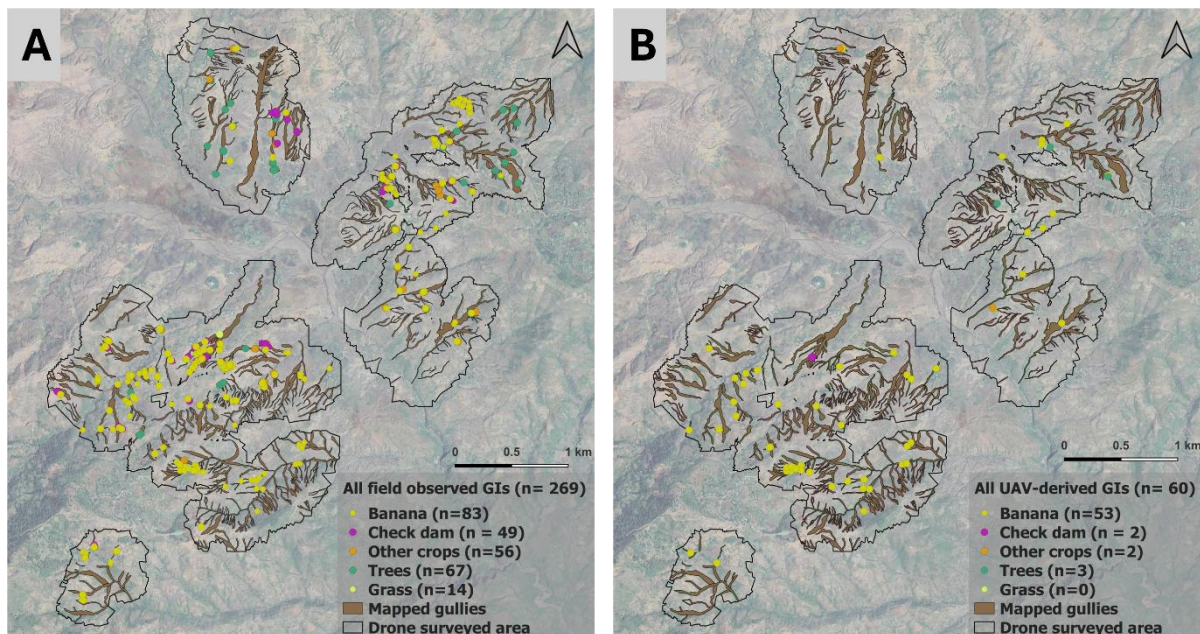


Figure A1: Spatial distribution of (A) all field observed gully interventions and (B) all UAV-derived gully interventions grouped into the main categories in the UAV-surveyed area. Background imagery: © Esri World Imagery.

Table A3: Full overview of individual gully interventions reported in the household survey (n=1,045).

Farming (n=439)	n	Physical (n=409)	n	Grasses (n=197)	n
Banana	189	Stone check dam	369	Desho grass (Pennisetum pedicellatum)	115
Eucalyptus	93	Wood check dam	31	Elephant grass (Pennisetum purpureum)	74
Sugar cane	38	Biological dam	8	Natural grass / local grass	3
Sorghum	22	Gabion check dam	1	Durisa	2
Chat	18			Sura	1
Casava	13			Chulla	1
Tid	8			Vetiver grass (Chrysopogon zizanioides)	1
Borto	7				
Barley	6				
Taro	6				
Haricot bean	4				
Sweet potato	3				
Bisana	3				
Enset	3				
Grevillea	3				
Wheat	3				
Grass	3				
Godariya	2				
Bolka	2				
Terminalia	2				
Korchi	2				
Wanza	2				
Teff	1				
Mango	1				
Woyira	1				
Onion	1				
Coffee	1				
Warka	1				
Shollo	1				

Appendix B: Spatial logistic regression model

Table B1: Non-significant and less discriminative spatial variables excluded from univariate screening.

Variable	Spearman r	p-value	Significance
Non-significant variables			
Elevation (m a.s.l.)	-0.000	9.90e-01	ns
Mean slope (°)	0.020	5.84e-01	ns
log(Dist. secondary road) (m)	0.014	7.11e-01	ns
log(Dist. river) (m)	0.057	1.16e-01	ns
Weighted N 0-30cm (cg/kg)	0.049	1.81e-01	ns
KDE settlement pressure: less discriminative radii (significant but not retained)			
log(KDE settlement pressure 50m)	0.167	4.03e-06	***
log(KDE settlement pressure 300m)	0.257	8.05e-13	***
log(KDE settlement pressure 500m)	0.249	4.31e-12	***

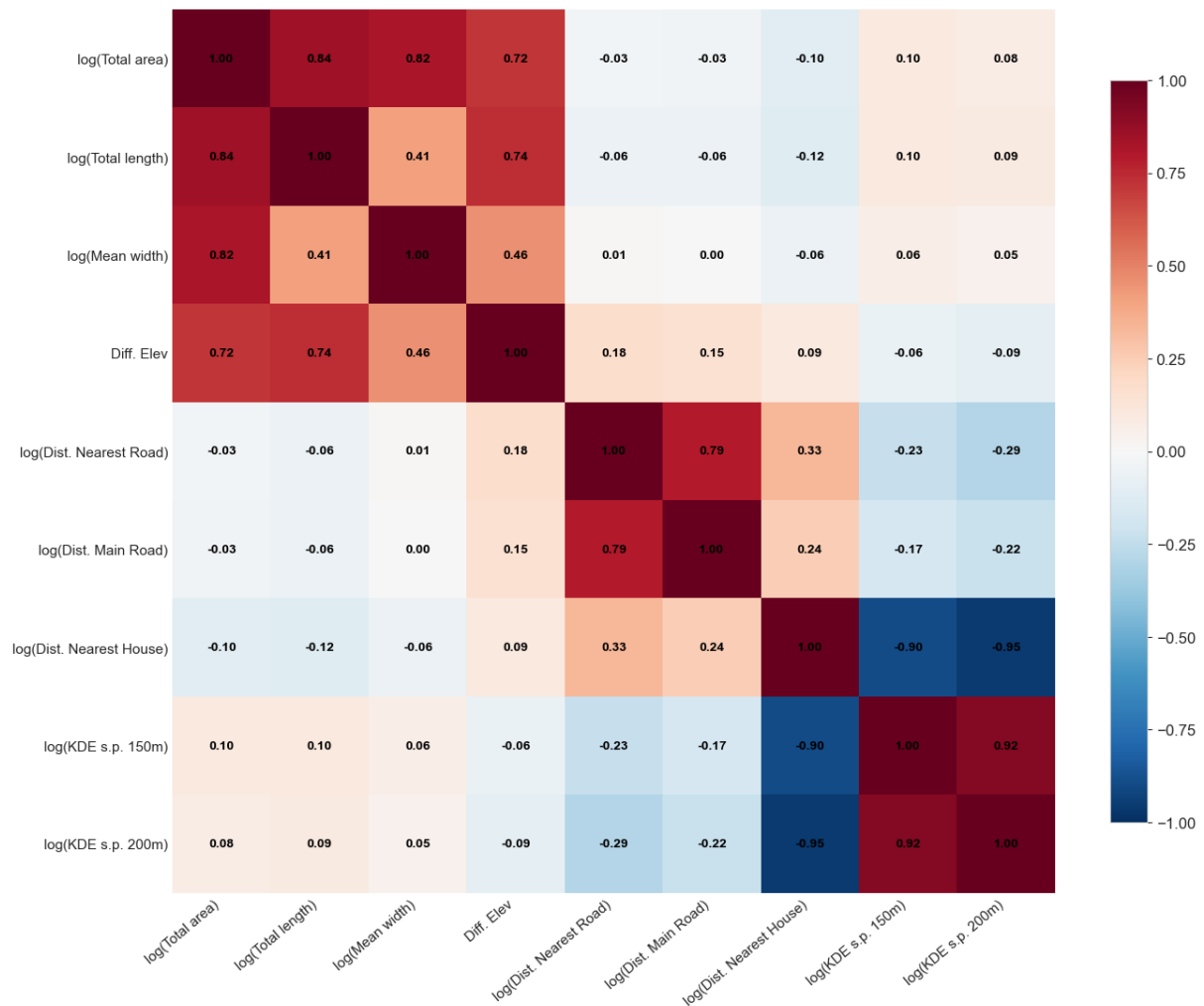


Figure B1: Spearman correlation matrix of retained spatial model variables.

Table B2: Classification outcomes and performance metrics of the spatial logistic regression model at the Youden threshold (0.126).

Metric	Youden threshold (0.126)	
	Confusion matrix	
True Positives		114
False Positives		231
False Negatives		21
True Negatives		385
	Classification metrics	
Sensitivity (Recall: treated)		0.844
Specificity (Recall: untreated)		0.625
Precision (treated)		0.330

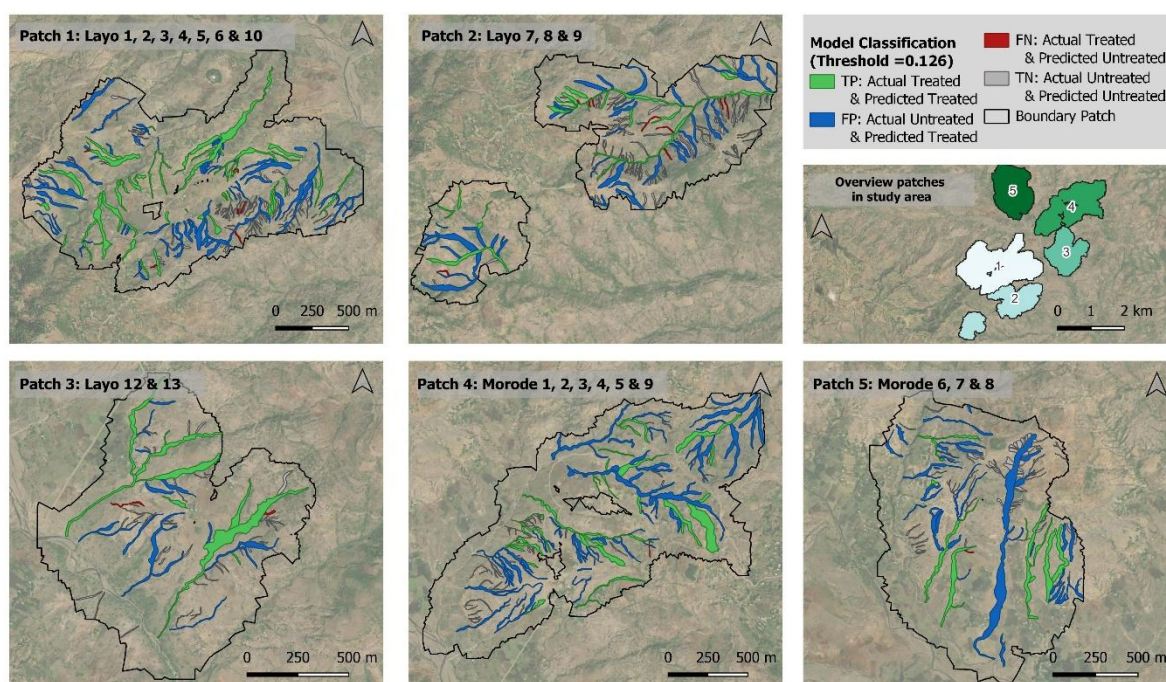


Figure B2: Spatial distribution of model classification outcomes across the five UAV-surveyed patches at the Youden threshold (0.126). Green = true positives (correctly identified treated gullies); blue = false positives (untreated gullies predicted as treated); red = false negatives (treated gullies missed by the model); grey = true negatives. Background imagery: Background imagery: © Esri World Imagery

Appendix C: Socio-economic logistic regression model

Table C121: Non-significant socio-economic variables excluded from univariate screening.

Variable	Level	n	Spearman r	p-value	Significance
Age of respondent	Farmer	988	-0.039	2.21e-01	ns
Log(household size)	Farmer	985	-0.025	4.26e-01	ns
Farming experience	Farmer	988	-0.028	3.85e-01	ns
Log(Income)	Farmer	945	-0.024	4.57e-01	ns
Prop. Plots with gully	Farmer	988	0.026	4.07e-01	ns
Education level	Farmer	984	-0.012	7.05e-01	ns
Land tenure	Plot	988	-0.017	5.93e-01	ns
Gully active	Gully	988	0.010	7.65e-01	ns

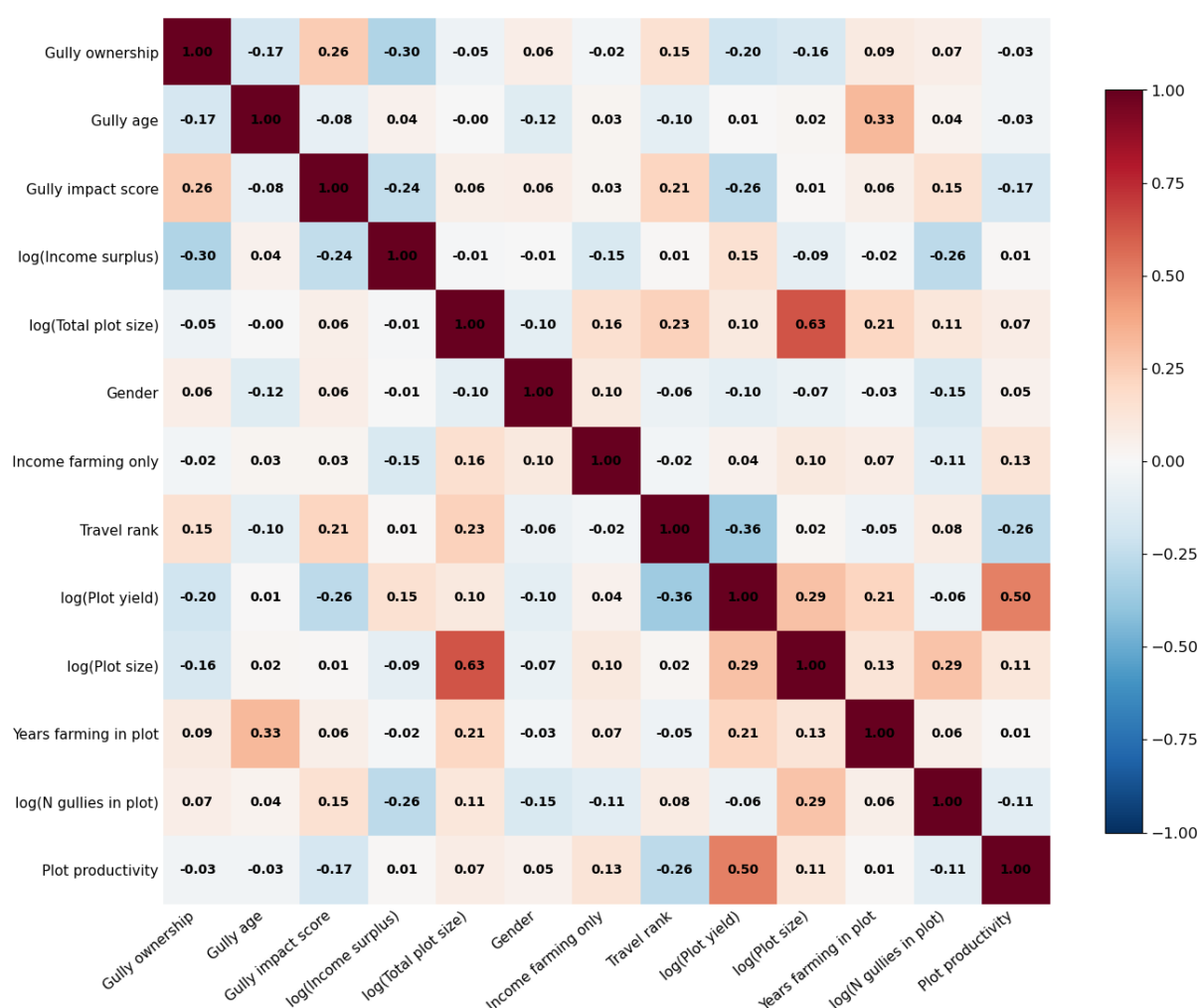


Figure C1: Spearman correlation matrix of retained socio-economic model variables.

Appendix D: Mixed logistic regression model

Table D122: Univariate Spearman correlations between candidate variables and gully treatment status in the linked dataset (D3, n=242). Variables are grouped by data source, n varies per variable due to missing values. Only variables tested in the mixed logistic regression model are shown; exposure variable excluded. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, ns = not significant

Variable	Source	n	Spearman r	p-value	Significance
log(Total area)	D1	242	0.456	7.74e-14	***
log(Total length)	D1	242	0.434	1.56e-12	***
log(Mean width)	D1	242	0.366	4.32e-09	***
log(Elev. diff.)	D1	242	0.366	4.27e-09	***
log(Dist. nearest road)	D1	242	-0.257	5.12e-05	***
log(Dist. main road)	D1	242	-0.150	1.94e-02	*
log(Dist. nearest house)	D1	242	-0.292	3.98e-06	***
log(KDE s.p. 150m)	D1	242	0.276	1.37e-05	***
log(KDE s.p. 200m)	D1	242	0.269	2.20e-05	***
Mean slope	D1	242	-0.068	2.95e-01	ns
Weighted N 0-30cm	D1	242	-0.187	3.42e-03	**
log(Income surplus)	D2	217	0.160	1.86e-02	*
log(Total plot size)	D2	241	-0.139	3.12e-02	*
log(Total gullies farmer)	D2	241	-0.168	9.14e-03	**
Age of respondent	D2	241	-0.083	2.00e-01	ns
Household size	D2	241	-0.065	3.16e-01	ns
Farming experience	D2	241	-0.104	1.06e-01	ns
Nr. of plots	D2	241	-0.032	6.16e-01	ns
Prop. plots with gully	D2	241	0.069	2.84e-01	ns
Education level	D2	241	-0.075	2.48e-01	ns
Gender	D2	241	0.112	8.15e-02	ns
Income farming only	D2	241	-0.034	6.03e-01	ns

Appendix E: Discrete-time hazard model

Table E1: Model fit statistics for $k=1$ to $k=10$ nearest neighbours in the neighbourhood exposure variable. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, ns=not significant.

k	OR	CI lower	CI upper	p-value	Sig.	Pseudo-R ²
1	7.852	3.974	15.514	3.00e-09	***	0.0230
2	6.061	3.314	11.084	4.91e-09	***	0.0248
3	7.705	4.562	13.012	2.24e-14	***	0.0446
4	7.642	4.597	12.703	4.42e-15	***	0.0498
5	6.605	3.986	10.945	2.38e-13	***	0.0455
6	7.679	4.650	12.680	1.64e-15	***	0.0579
7	7.002	4.227	11.598	4.11e-14	***	0.0537

8	6.343	3.820	10.532	9.24e-13	***	0.0491
9	6.167	3.690	10.306	3.81e-12	***	0.0479
10	6.797	4.015	11.508	9.70e-13	***	0.0530

In the main analysis, neighbourhood exposure was computed as the lagged sum of neighbour contributions, capped at 1 (Section 2.3.4). A potential concern is that this variable encodes both genuine local spatial diffusion and the general temporal increase in GI adoption over time: because more neighbours will have adopted simply as time progresses, the exposure score tends to rise regardless of any local diffusion effect. This temporal confounding was addressed in Models C and D by including the calendar year as a covariate.

An alternative approach is to remove the time trend from the exposure variable itself by dividing the raw neighbour sum by $CDF(t-1)$, which represents the background probability that any gully in the catchment had already adopted by year $t-1$. Under this normalisation, a value of 1 means that neighbours adopted at exactly the same rate as the catchment average, while values above 1 indicate that neighbours adopted faster than average, a signal that is by construction independent of the overall time trend. For years where $CDF(t-1) < 0.01$, the ratio becomes numerically unstable due to near-zero adoption in the earliest years of the panel; exposure was therefore set to zero for those rows. Results are shown in Tables E2 and E3.

Table E2: Standardised odds ratios, 95% CI, p-values and VIF for models F and G (CDF-normalised exposure variable)

Variable	OR	CI low	CI high	p-value	Sig.	Bonf.	VIF
Model E: Only CDF-normalised exposure							
Norm. Lag. exposure (k=6)	1.18	1.074	1.295	5.25e-04	**	*	1
Model F: CDF-normalised exposure and spatial variables							
Norm. Lag. exposure (k=6)	1.074	0.955	1.208	2.31e-01	ns	ns	1.06
log(Area)	1.867	1.536	2.369	3.70e-10	***	*	1.02
log(Dist. road)	0.670	0.546	0.823	1.31e-04	***	*	1.07
log(KDE 200m)	1.441	1.171	1.772	5.53e-04	***	*	1.09

Table E323: Model statistics for models F and G (CDF-normalised exposure variable)

	Model E: CDF-normalised exposure only	Model F: CDF-normalised exposure and spatial variables
Pseudo-R ²	0.0069	0.0848
AIC	984.73	913.8
AUC (10-fold CV)	0.665 ± 0.107	0.799 ± 0.088

Appendix F: Ethical approval



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To whom it may concern

PRET approval number: G-2025-9211

Title: **Mapping and understanding farmers' responses to gully-induced problems in the Abaya-Chamo Lakes Catchment, Southern Ethiopia.**

Principal investigator: Yibeltal Yihunie Mekonnen

Leuven: 2025-05-08

GDPR compliance and ethical approval

The above-mentioned project application was submitted to KU Leuven's Privacy and Ethics platform (PRET). The project application was scrutinized in view of principles and obligations laid down in the General Data Protection Regulation of the European Parliament and of the Council of 27 April 2016. Based on the information presented and given the researcher's explicit declaration that the project will be carried out accordingly, KU Leuven issued a favorable advice and confirmed that the project may be implemented as such.

All relevant information concerning the processing of personal data in the framework of this project has been registered in KU Leuven's records of processing activities.

The project application was also reviewed by the Social and Societal Ethics Committee (SMEC) of KU Leuven. The Committee confirmed that the project application meets the expected ethical standards regarding the voluntary involvement of human participants in scientific research. SMEC's decision regarding this protocol is favourable.

Yours sincerely

Digitally confirmed by Toon Boon (data protection officer) and Dieter Baeyens (chair SMEC)

Appendix G: The household questionnaire

Farmers' responses to gully-induced problems, Shafe Catchment, southern Ethiopia

2025

Dear Sir/Madam,

We are conducting a research in collaboration with Arba Minch University and Katholieke Universiteit Leuven (KU Leuven), funded by the Belgian University Development Cooperation (VLIRUOS). You have been selected to provide essential information for understanding the farmers' responses to gully-induced problems and decision-making process. All the information you provide will be kept confidential and used solely for research purposes. We kindly request that you discuss this with us in a trustful and faithful manner.

Are you willing to participate? Yes ☐ No ☐

Thank you in advance for your cooperation!

Section I: General information & demographic characteristics

S.no	Questions	Response
1.1	Date and time of the interview (ቀን)	(automatic)
1.2	Keble name (የቀበሌ ሥም)	
1.3	Name of enumerator (የምረጃ ሰብሳቢው ስም)	
1.4	GPS location	(automatic)
1.5	Household ID	
1.6	Name of the respondent (የምላሽ ሰጪው ስም)	
1.7	Gender of the respondent (1. Male / 2. Female / 3. Other) (የምላሽ ሰጪው ጾታ)	
1.8	Age of the the respondent (years) (የምላሽ ሰጪው አድሜ)	
1.9	Marital status of the respondent (code 1a) (የምላሽ ሰጪው የጋብቻ ሁኔታ)	
1.10	Level of education of the respondent (code 1b) (የምላሽ ሰጪው የትምህርት ደረጃ)	
1.11	Total size of household (number of people in the household) (የቤተሰብ ብዛት)	
1.12	Years of farming experience (years) (ምን ያህል ዓመት በእርሻ ላይ ቆይቶ)	

Code 1a	Code 1b
Single (ያለገብ)	Not able to read and write
Married (ያገብ)	Basic (able to read and write with no formal education)
Divorced (የተፋታ)	Primary school
Widowed (በል የሞተበት)	Secondary school
	Graduate
	Other (specify):

Section II: Household economic status and assets

- What are the main sources of income for your household? (Select all that apply – code 2a) (ለቤተሰብዎ ዋና የገቢ ምንጮች ምንድናቸው?) (የሚመለከተውን ሁሉ ይምረጡ)
- What is the estimated total annual income of your household (in Ethiopian Birr)? (የቤተሰብዎ አጠቃላይ ዓመታዊ ገቢ ምን ያህል ይገመታል?)
- Who owns the house your household currently lives in? (code 2b) (የእርስዎ ቤተሰብ በአሁኑ ጊዜ የሚኖርበት ቤት ማን ነው ያለው?)
- What type of house does your household live in? (code 2c) (በምን አይነት ቤት ነው የሚኖሩት?)
- Which of the following types of livestock does your household own? (code 2d) (ከሚከተሉት የእንስሳት ዓይነቶች ውስጥ የትኛው አለዎት?)

Code 2a	Code 2b	Code 2c	Code 2d	
Farming (እርሻ) Trade (ንግድ) Employment (የመንግስት ቅጥር) Daily labor (የቀን ሥራ) Remittances from family members (ከቤተሰብ አባላት የሚላከው ገንዘብ) Handicrafts (e.g., weaving, pottery) (የእጅ ሥራዎች (ለምሳሌ ሽመና፣ ሽክላ) Sale of firewood or charcoal (የማገዶ እንጨት ወይም የድንጋይ ከሰል ሽያጭ) Other (specify) (ሌላ): _____	Owned by the household (የራሳችን) Rented (የኪራይ) Shared with family (ከቤተሰብ ጋር አብረን የምንጋራው) Provided by relatives/friends (በዘመዶች/ዳደሮች የተሰጠን) Other (specify) (ሌላ): _____	Hatched and wooden wall (የሳር ከዳን እና የእንጨት ግድግዳ) Corrugated iron roofed and wooden walls (የቆርቆሮ ከዳን እና የእንጨት ግድግዳ) Corrugated iron roofed and brick walls (የቆርቆሮ ከዳን እና የብሎኬት ግድግዳ) Other (specify) (ሌላ): _____	Livestock type Oxen (በሬ) Cow (ላም) Sheep (በግ) Goat (ፍየል) Horse (ፈረስ) Donkey (ፈረስ) Poultry (ዶሮ) Beehives (የንብ ቀፎዎች) Other (specify) (ሌላ): _____	Number owned (ስንት)

Section III: Landholding size, tenure, land productivity and presence of gullies

- How many agricultural plots does your household currently own? (ያለዎት አጠቃላይ የእርሻ ቦታ ብዛት) _____
- For each of your plots, could you please provide details on the plot size, land tenure type, farming practices used, and whether there are any gullies

Plot no (የቦታ ቁጥር)	Plot size (ሞገን)		Land tenure status (የመሬት ይዞታ ሁኔታ) (code 3b)	For how many years have you been farming in this plot? (ቦታውን ለስንት ዓመት አረሱት) (number of years)	Which of the following crops did you produce last ? (ባለፈው ዓመት ምን ምን ስብሎችን አመረቱ) (code 3c)	What was the total yield from this plot last year? (ባለፈው ዓመት ከዚህ መሬት የተገኘው አጠቃላይ ምርት ምን ያህል ነበር? (በኪ.ግ.) (in kg)	How would you describe the productivity of your plot? (የዚህን መሬትን ምርታማነት እንዴት ይገልጹታል?) (code 3d)	How far is the plot from your home? (estimate in km) (ማሳውቁ ከቤትዎ ምን ያህል ይርቃል? ምን ያህል እንደሚፈጅ በደቂቃዎች ወይም ሰዓቶች ገምቱ)	Are there gullies in this plot? (በዚህ ማሳ ላይ ገሊ/ቦረቦር አለ?) (1. Yes/ 0. No)	If yes, how many gullies are there? (ስንት?)
	Amount	Unit (መለኪያ) (code 3a)								

Code 3a	Code 3b	Code 3c	Code 3d
Hactare Timad m²	Owned (certified) (በባለቤትነት የተያዘ ; የተረጋገጠ) Owned (not certified) (በለቤትነት ; ያልተረጋገጠ) Rented (የኪራይ) Leased (የሊዝ) Communal (የወል መሬት) Other (ሌላ)	Maize (ብቆሎ) Sorghum (ማሽላ) Teff (ጢፍ) Wheat (ስንዴ) Barley (ጉብስ) Potato (ድንች)	Sweet potato (ስኳር ድንች) Faba been (ባቄላ) Haricot bean (ቦላቄ) Banana (ሙዝ) Check pea (ሽምብራ) Cassava (እንጨት ቦዴ) Other (ሌላ)
			Highly productive (በጣም ምርታማ) Moderately productive (መካከለኛ) Low productivity (ዝቅተኛ ምርታማነት) I don't know (አላውቅም) (ለመግለጽ እችላለሁ)

Section IV : Gully dynamics, size and impacts

4.1. In summary, do you have at least one gully on one of your plots? (ካሉት ማሳዎች መካከል ቢያንስ በአንዱ ቦረቦር/ገሊ አለ?)

Gully information per plot of land (ask this question for plots having gullies) (ቦረቦር/ገሊ ላላቸው ማሳዎች ብቻ የሚጠየቅ ነው)

Plot no (የቦታ ቁጥር)	Gully no (የገሊ ቁጥር)	How many years ago was the gully first observed? (ለመጀመሪያ ጊዜ ይህን ገሊ መቼ ነው በማሳዎ ላይ የተመለከቱት/ያዩት)	Is the gully currently active? (ገሊው በአሁኑ ሰዓት መሬትዎን እየጎዳ/እየሸረሸረ ነው ወይንስ እየቆመ ነው) (1. Yes/ 0. No)	Who owns the gully? (ገሊው በአኗኗሩ መሬት ላይ ብቻ ነው የሚገኘው ወይንስ ከሌሎች ጋር ነው የሚጋሩት) (code 4a)	To what extent do you think this gully affects you (e.g., land loss or crop yield reduction)? (ይህ ቦረቦር/ገሊ ምን ያህል ጉዳት እያደረሰሰኝ ነው ብለው ያስባሉ (ለምሳሌ: የመሬት በመውሰድ (በማሳጣት) ወይም የሰብል ምርት በመቀነስ)? (Code 4b)	What are the biggest impacts this gully has on your land or livelihood Select maximum 3 (ይህ ቦረቦር/ገሊ በመሬትዎ ወይም በኑሮዎ ላይ ያመጣው ትልቅ ተጽእኖ ምንድን ነው? 3 ይምረጡ) (Code 4c)	Have you taken any measures on the gullies themselves? (ገሊው ውስጥ የሰሩት ሥራ አለ) (1. Yes/ 0. No)	Have you implemented SWC measures on the upslope land to reduce runoff accumulation towards the gully? (ከገሊው በላይ ባለው መሬት ጎርፍን ለመቀነስ የሰሩት ሥራ አለ) (1. Yes/ 0. No)

Code 4a	Code 4b	Code 4c
It is mine (የእኔ ነው/በእኔ ማሳ ነው ያለው) Shared by the landowners along the gully (የጋራ ነው/የመንግስት ነው) It is communal & owned by government (ባለመሬቶች/ገሊው ያለባቸው/ ሰዎች የጋራ ነው) Other (ሌላ)	Very severe impact (በጣም ከፍተኛ ተጽዕኖ) Severe impact (ከፍተኛ ተጽዕኖ) Moderate impact መካከለኛ ተጽዕኖ) Slight impact (ዝቅተኛ ተጽዕኖ) No impact (ምንም ተጽዕኖ የለውም)	Direct loss of crop land (የሰብል መሬት በቀጥታ ማጣት) Crop yield reduction (የምርት መቀነስ) Buffer requirements (በገሊዎች እካባቢ የተወሰነ መሬት እንድንተው ማስገደድ) Loss of grazing land (የግጥሽ መሬት መቀነስ) Sediment flow into fields (ወደ ማሳዎች ደለል መግባት) Increased flooding (የጎርፍ መጥለቅለቅ መጨመር) I'm not impacted by it (ምንም ተጽዕኖ የለውም)

		Affect mobility/trafficability (ከቦታ ቦታ መንቀሳቀስ ላይ ተጽዕኖ ማሳደር)	Other (ሌላ) _____
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Section V: Farmers' responses to gully induced problems and actors involved - CONTINUE PER PLOT PER GULLY

5.1. If you have taken measures on the **gullies themselves**, what types of measures have you implemented?

5.1.1. Have you tried farming in the gully? (ገሊው ውስጥ የእርሻ ሥራ ሞክረዋል) (1. Yes/ 0. No)
If yes, what motivates you to start farming inside the gully? (code 5a) (ገሊው ውስጥ የእርሻ ሥራ እንድትጀምሩ ያነሳሳህ ምንድን ነው?)
What types of plants/crops have you planted? (code 5b) (ምን ዓይነት እጽዋት/ሰብል)
Who convinced you to plant these specific plants/crops? (code 5c) (እነዚህን ተክሎች/ሰብሎች እንድትተክሉ ያሳመናችሁ ማን ነው?)
For how many years have you been practicing farming in the gully? (years) (ለምን ያህል አመታት ገሊው ውስጥ የእርሻ ሥራ ሰርቷል)
Are the cropping times inside the gully similar to the cropping times of your other fields/crops? (1. Yes/ 0. No) (በገሊ ውስጥ ያለው የሰብል ጊዜ ከሌሎች እርሻዎች/ሰብሎች የሰብል ጊዜ ጋር ተመሳሳይ ነው?)
If yes, what is the difference in cropping times? (ልዩነቱ ምንድን ነው?)
Have you received any support to starting farming in the gully? 1. Yes/ 0. No) (በገሊው ውስጥ እርሻ ሥራን ለመስራት ድጋፍ አግኝተዋል?)
If yes, who provided support? (code 5d) (ማን ነው ድጋፍን ያደረገው?)
What type of support have you received? (code 5e) (ምን ዓይነት ድጋፍ ነው ያገኙት?)
How many attempts were made to start farming inside the gully? (number) (በገሊ ውስጥ እርሻ ለመጀመር ስንት ሙከራዎች አድረገዋል?)
What were the challenges you encountered when implementing this measure? (code 5g) (ይህንን ሥራ ሲተገብሩ ያጋጠሙዎት ዋና ዋና ፈተናዎች ምን ምን ነበሩ? (በገሊ ውስጥ እርሻ)
Does the farming inside the gullies currently work? (1. Yes/ 0. No) (በገሊ ውስጥ ያለው የእርሻ ሥራ በአሁኑ ሰዓት ውጤታማ ነው)
If yes, what positive impacts have you observed/experienced? (code 5f) (ምን አዎንታዊ ተፅዕኖዎችን አስተውለዋል?)
5.1.2. Have you built any physical measures inside the gully? (1. Yes/ 0. No) (በገሊው ውስጥ አካላዊ ሥራዎች ገንብተዋል)
If yes, what type of measures have you implemented? (code 5h) (ምን ዓይነት ሥራዎች)
What motivates you to build such physical measures inside the gully? (code 5a) (በገሊው ውስጥ አካላዊ ሥራዎች እንድትጀምሩ ያነሳሳህ ምንድን ነው?)
Who convinced you to build those measures? (code 5c) (አካላዊ ሥራዎች እንድትሰሩ ያሳመናችሁ ማን ነው?)
How old are those implemented physical measures? (years) (እነዚህ አካላዊ ሥራዎች ምን ያካል አመት ይሆናቸዋል)
Have you received any support to built such measures? 1. Yes/ 0. No) (በገሊው ውስጥ አካላዊ ሥራን ለመስራት ድጋፍ አግኝተዋል?)
If yes, who provided support? (code 5d) (ማን ነው ድጋፍን ያደረገው?)
What type of support you received?(code 5e) (ምን ዓይነት ድጋፍ ነው ያገኙት?)
How many attempts were made to built such measures inside the gully? (number) (እነዚህን ሥራዎች ለመስራት (አካላዊ ሥራዎች) ምን ያካል ሙከራዎች አድረገዋል)

What were the challenges you encountered when implementing this measure? (code 5g) (ይህንን ሥራ ሲተገብሩ ያጋጠሙዎት ዋና ዋና ፈተናዎች ምን ምን ነበሩ? (አካላዊ ሥራዎች)
Do the measures inside the gullies currently work? (1. Yes/ 0. No) (በገሊ ውስጥ ያለው አካላዊ ሥራ በአሁኑ ሰዓት ውጤታማ ነው)
If yes, what positive impacts have you observed/experienced? (code 5f) (ምን አዎንታዊ ተፅዕኖዎችን አስተውለዋል?)
5.1.3. Have you planted any grass in the gully? (1. Yes/ 0. No) (ገሊው ውስጥ ሰር ተክለዋል)
If yes, what type of grass species have you planted? (code 5i) (እዎ ከሆነ ምን ዓይነት ሰር)
What motivates you to plant such grass? (code 5a) (ገሊው ውስጥ ሰር ለመትከል ያነሳሳህ ምንድን ነው?)
Who convinced you to select these specific grasses? (code 5c) (ሰር እንድትተክሉ ያሳመናችሁ ማን ነው?)
For how many years have you been practicing planting a grass in the gully? (years) (ምን ያህል አመታት ይሆናል ሰር መትከል ከጀመሩ)
Have you received any support to plant grass in the gully? 1. Yes/ 0. No) (በገሊው ውስጥ ሰር ለመትከል ድጋፍ አግኝተዋል?)
If yes, who provided support? (code 5d) (ማን ነው ድጋፍን ያደረገው?)
What type of support you received? (code 5e) (ምን ዓይነት ድጋፍ ነው ያገኙት?)
How many attempts were made to plant grass inside the gully? (number) (በገሊ ውስጥ ሰር ለመትከል ምን ያካል ሙከራዎች አድረገዋል?)
What were the challenges you encountered when implementing this measure? (code 5g) (ይህንን ሥራ ሲተገብሩ ያጋጠሙዎት ዋና ዋና ፈተናዎች ምን ምን ነበሩ? (ሰር መትከል)
Does the planting grass in the gullies currently work? (1. Yes/ 0. No) (በገሊ ውስጥ ያለው ሰር በአሁኑ ሰዓት ውጤታማ ነው)
If yes, what positive impacts have you observed/experienced? (code 5f) (ምን አዎንታዊ ተፅዕኖዎችን አስተውለዋል?)

Code 5a	Code 5b	Code 5c	Code 5d	Code 5f
Personal motivation to rehabilitate the gully (የግል ተነሳሽነት)	Banana (ሙዝ)	My own decision (የራሴ ውሳኔ)	Family members (የቤተሰብ አባላት)	Reduced soil loss (የአፈር ብክነት መቀነስ)
Community practice/neighbors farmers (ማህበረሰብ /አገራባች ገበሬዎች)	Sweet potato (ስኳር ድንች)	Encouraged by neighbors/community practices (ማህበረሰብ /አገራባች ገበሬዎች)	Neighboring farmers (ሳረሲት)	Rehabilitation of the gully (የገሊው መልሶ ማገገም)
Land scarcity & need for more land (የመሬት አጥረት እና ተጨማሪ የመሬት ፍላጎት)	Sugar cane (ሸንኮራ)	Based on government/NGO recommendations but voluntarily adopted (በመንግስት/መንግስታዊ ያልሆኑ ድርጅቶች ምክሮች ላይ በመመስረት ግን በፈቃደኝነት)	Government (መንግስት) (ቀበሌ ግብርና)	Decreased sediment flow into fields & water bodies (ወደ ማሳዎች እና የውሃ አካላት የደረሰ ፍሰት መቀነስ)
Moisture availability in the gully (በገሊው ውስጥ የተሻለ እርጥበት መኖር)	Sorghum (ማሽላ)	Required or strongly advised by government/NGO programs (በመንግስት/መንግስታዊ ባልሆኑ ፕሮግራሞች ፍላጎት)	NGOs (መንግሥታዊ ያልሆኑ ድርጅቶች)	Reduced flooding (የጎርፍ መቀነስ)
Economic benefits (ኢኮኖሚያዊ ጥቅሞች)	Eucalyptus (ባህርዝፍ)	Implemented as part of a project without direct farmer involvement (በቀጥታ በፕሮጀክት ድጋፍ የተተገበረ ካለ እርሶ አደሮች ተሳትፎ)	Religious institutions (የሃይማኖት ተቋማት)	Economic benefit or income (የኢኮኖሚ ጥቅም ወይም ገቢ ማግኘት)
Government/NGO encouragement (የመንግስት/መንግስታዊ ያልሆኑ ድርጅት ማበረታቻ)	Casava (እንጨት በቄ)		Community organizations (የማህበረሰብ ድርጅቶች)	Fodder for livestock (የከብቶች መኖ)
Other (ሌላ)	Other (ሌላ)	Other (ሌላ)	Ot her (ሌላ)	Other (ሌላ)

Code 5g	Code 5h	Code 5i	Code 5j	Code 5e
Poor soil condition in the gully (ጥፋ ያልሆነ የአፈር ሁኔታ) Inappropriate choice of plant/crop species (ትክክለኛ ያልሆነ የእጽዋት/ሰብል ምርጫ) Unavailability of water for plants/crops (ለተከላኤ/ሰብላኤ ውሃ አለመገኘት) Inappropriate choice of grass species (ትክክለኛ ያልሆነ የሳር ምርጫ) Lack of regular maintenance (መደበኛ የጥገና እሳረት) Inadequate design (በቂ ያልሆነ ዲዛይን) Resources limitation for proper implementation and maintenance (የሃብት እሳረት) Lack of technical supports from government/NGOs (ከመንግስት/መንግስታዊ ያልሆኑ ድርጅቶች የቴክኒክ ድጋፎች እሳረት) Other (ሌላ) I encountered no challenges (ምንም ፈተናዎች አላጋጠሙኝም)	Stone check dam (የድንጋይ ግድብ) Wood check dam (የእንጨት ግድብ) Gabion check dam (በጋቢወን የተሰራ ግድብ) Other (ሌላ)	Desho grass (Pennisetum pedicellatum) (ዴሾ ሳር) Vetiver grass (Chrysopogon zizanioides) (ቪቲቨር ሳር) Elephant grass (Pennisetum purpureum) (ግሪፍ ሳር) Other (ሌላ)	Stone bunds (የድንጋይ እርከን) Terracing (የአርከን ስራ) Soil bunds (የአፈር እርከን) Tree planting (ዛፍ መትከል) Trenches (ቦይ) Other (ሌላ)	Training/capacity building (ሥልጠና) Financial support (የገንዘብ ድጋፍ) Material support (የቁሳቁስ ድጋፍ) Technical guidance (የቴክኒክ ድጋፍ) Labor assistance (የጉልበት ድጋፍ) Information (መረጃ) Other (ሌላ)

5.2. If you implemented SWC measures on **the upslope land**, what types of measures have you implemented?

If yes, what motivates you to start implemented SWC measures on the upslope land? (code 5a) (ከገሊው በላይ ባለው መሬት ጎርፍን ለመቀነስ የሰፋትን ሥራ ለመስራት ማን አነሳሰችሁ?)
What types of measures have you implemented? (code 5j) (ከገሊው በላይ ባለው መሬት ጎርፍን ለመቀነስ የሰፋት ሥራ ካለ ምን ዓይነት ሥራዎች?)
Who convinced you to implement these SWC measures on the upslope land? (code 5c) (ያሰመናችሁ ማን ነው?)
For how many years have you been practicing farming in the gully? (years) (ምን ያክል አመት ሆኗል)
Have you received any support to implement such measures? 1. Yes/ 0. No) (ድጋፍ አግኝተዋል)
If yes, who provided support? (code 5d) (ማን ነው ድጋፍን ያደረገው?)
What type of support you received? (code 5e) ((ምን ዓይነት ድጋፍ ነው ያገኙት)

How many attempts did you make to implement SWC measures on the upslope land? (number) (ምን ያክል ሙከራዎች አደርገዋል)
What were the challenges you encountered when implementing this measure? (code 5g) (ይህንን ሥራ ሲተገብሩ ያጋጠሙዎት ዋና ዋና ፈተናዎች ምን ምን ነበሩ?)
Do the measures currently work? (1. Yes/ 0. No) (አሁን ላይ ውጤታማ ናቸው)
If yes, what positive impacts have you observed/experienced? (code 5f) (ምን አዎንታዊ ተፅዕኖዎችን አስተውለዋል)

Section VI: Farmers' participation and SWC preferences

6.1. Workshop Participation and learning:

6.1.1. Have you recently attended a workshop or training where information about implementing SWC measures in gully systems was provided? (በቅርቡ በተካሄደው ወርክሾፕ/ስብሰባ ላይ ተካፋይ ነበሩ በገሊ መልሶ ማገገም ዙሪያ?)
If yes, did this workshop change your understanding of gullies and/or SWC? (code 6a) (ይህ አውደ ወርክሾፕ/ስብሰባ ስለ ጉሊ እና/ወይም አፈር እና ውሃ ጥበቃ ሥራ ያለዎትን ግንዛቤ ለውጥታል?)
Has this workshop changed the way you would approach implementing SWC measures? (1. Yes/ 0. No) (ይህ ወርክሾፕ የአፈር እና ውሃ ጥበቃ ሥራዎችን በመተግበር የምትሄድበትን መንገድ ለውጥታል?)
If yes, can you please specify what you plan to do differently as a result of this workshop? (በዚህ ወርክሾፕ ምክንያት የተለየ ለማድረግ ያቀዱትን አባከዎን ይግለጹ?)

Code 6a
Much more knowledge (ብዙ ተጨማሪ እውቀት)
Somewhat more knowledge (ትንሽ ተጨማሪ እውቀት)
No change in knowledge (በእውቀት ላይ ምንም ለውጥ የለም)
Less sure now (አሁን ላይ እርግጠኛ አይደለሁም)

6.2. Ranking of Factors Influencing SWC Implementation in Gullies:

6.2.1 Please rank the following factors from **1 (most important)** to **4 (least important)** based on how they influence your decision to implement SWC measures inside gullies. (እባክዎን በገሊ ውስጥ የአፈር እና ውሃ ጥበቃ ሥራዎችን ለመተግበር ባደረጉት ውሳኔ ላይ ተጽዕኖ ያሳደሩትን አካላት/ተግባራት ደረጃ ይስጡ)

Factors	Ranking
Financial and material reasons (የገንዘብ እና ቁሳዊ ምክንያቶች)	
External Influences (ውጫዊ ተጽእኖዎች)	
Land Characteristics (ከመሬቱ ባህሪ ጋር የተገናኙ)	
Gully Characteristics (የገሊ ባህሪያት)	
Knowledge and perception (እውቀት እና ግንዛቤዎች)	

6.2.2. For each of the groups you just ranked, please rank the sub-factors within that group from 1 (most important) to x (least important), based on how they influence your decision to implement SWC measures inside gullies.

Financial and material reasons (የገንዘብ እና ቁሳዊ ምክንያቶች)	Ranking
Personal financial ability to invest in SWC (በአፈር እና ውሃ ሥራዎች ላይ ኢንቨስት ለማድረግ የግል የፋይናንስ አቅም)	
Material support (stones, seedlings etc.) (የቁሳቁስ ድጋፍ (ድንጋዮች ፣ ችግኞች ፣ ወዘተ.))	
Financial support (የገንዘብ ድጋፍ)	
Manpower to implement the SWC measure (የሰው ሃይል/ጉልበት የአፈር እና ውሃ ሥራዎችን ለመስራት)	

External Influences (ውጫዊ ተጽእኖዎች)	Ranking
Community /neighboring farmers practice (የማህበረሰብ/አገራባች ገበሬዎችን በመመልከት)	
Government/NGO encouragement (የመንግስት/መንግስታዊ ያልሆነ ድርጅት ማበረታቻ)	

Land Characteristics (ከመሬቱ ባህሪ ጋር የተገናኙ)	Ranking
Land ownership (የመሬት ባለቤትነት)	
Landholding size/total land owned by the farmer (የመሬት ይዘታ መጠን/ አጠቃላይ በገበሬው የተያዘ መሬት)	
Proximity to homesteads (ለመኖሪያ ቤቶች ያለው ቅርብነት)	
Land productivity (የመሬቱ ለምትነት)	

Gully Characteristics (የገሊ ባህሪያት)	Ranking
Gully size (የገሊ መጠን)	
Gully activity (የገሊ ሁኔታ)	

Knowledge and Perception (እውቀት እና ግንዛቤዎች)	Ranking
Opportunities and perceived positive impacts (እድሎች እና ታሰቢ የተደረጉ አዎንታዊ ተጽእኖዎች)	
Knowledge and awareness (እውቀት እና ግንዛቤ)	
To tackle the negative perceived impacts (አሉታዊ ተፅእኖዎችን ለመቋቋም)	

6.3. Preferred SWC measures

6.3.1. Which measures are you most interested in applying in the future? (code 6b) (ለወደፊት የትኞቹን የአፈር እና ውሃ ጥበቃ ሥራዎችን ለመተግበር ነው ፍላጎትዎ? (ከገሊ ጋር በተያያዘ)
6.3.2. Can you explain why you would prefer this measure(s) compared to the other options? (code 6c) (ለምን እንደሆነ የአፈር እና ውሃ ጥበቃ ሥራዎች ለመስራት እንደመረጡ ማብራራት ይችላሉ)

Code 6b	Code 6c	
Planting crops (like banana) in the gully (በገላው ውስጥ ስብሎችን (እንደ ሙዝ) መትከል)	It is financially more affordable option in terms of labour (ከጉልበት/ከሰው ሃይል አስፈላጊነት አንጻር የተሻለ ስለሆነ - ብዙ የሰው ሃይል ስለማይፈልግ)	I have the knowledge and skills to implement this option effectively (ይህንን አማራጭ በብቃት ለመተግበር ዕውቀት እና ችሎታ አለኝ)
Planting grass in gully (በገላው ውስጥ ሰር መትከል)	It is financially more affordable option in terms of material (ከቁሳቁስ አቅርቦት አንጻር የተሻለ ስለሆነ)	It is encouraged by external support (projects/government) (በውጭዊ ድጋፍ (ፕሮጀክቶች/መንግስት) ይህን እንድንተገብር ስለምንበረታታ)
Stone check dams (የድንጋይ ግድብ)	it is a more suitable option considering gully characteristics (ከገላው ባህሪያት አንጻር የበለጠ ተስማሚ አማራጭ ስለሆነ)	it is applied by neighboring farmers (በአከገብ ያለ ጎሮሴቱ ከዚህ በፊት ስለተገበረው)
Wooden check dams (የእንጨት ግድብ)	It provides quick benefits (ከተሰራ በኋላ በቅሎ ጥቅም ስለሚሰጥ)	Other (ሌላ)
Gabion check dams (በጋቢውን የተሰራ ግድብ)		
Planting trees or vegetation in the gully (በገላው ውስጥ ዛፍ መትከል)		
Applying upslope SWC measures (ከገላው በላይ ባለው መሬት የአፈር እና ውሃ ጥበቃ ሥራዎችን መስራት)		
I'm not interested in applying SWC measures in the future (ወደፊት ምንም ለመስራት ፍላጎት የለኝም)		
Other (ሌላ)		

Section VII: Final remarks and debriefing

6.1. Can you describe how you made the decision to implement SWC measures inside the gully? What were the key reasons behind your decision?

(በገላው ውስጥ የአርን ውሃ ጥበቃ ሥራዎችን ለመስራት እንዴት እንደወሰነ መግለጽ ይችላሉ? ከውሳኔዎ ጀርባ ዋና ዋና ምክንያቶች ምን ነበሩ?)

6.2. Why have some gullies on your land not been managed or rehabilitated? This question will be asked to households who have gullies on multiple plots but implemented SWC measures only on some.

(በአንዳንድ ማሰዎ ላይ ያሉ ገሊዎች ላይ ምንም ስራ ያልሰሩት ለምንድን ነው? ለምን የተወሰኑትን ብቻ መረጡ?)

6.3. What was the biggest challenge you faced when deciding to implement SWC measures? Give maximum 2 answers.

(በገላ መልስ ማግኘት ዙሪያ የአፈር እና ውሃ ጥበቃ ሥራዎች ለመስራት ሲወስኑ ያጋጠሙዎት ዋና ዋና ፈተናዎ ምን ነበሩ? ቢበዛ 3 መልሶች ይስጡ)

6.4. Based on your experience, what advice would you give to other farmers or policymakers about implementing SWC measures inside gullies?

(በተጭከሮዎ ላይ በመመስረት፣ በገላው ውስጥ የአርን ውሃ ጥበቃ ሥራዎችን ስለመተግበር ለሌሎች ገበሬዎች ወይም ፖሊሲ አውጪዎች ምን ምክር ይሰጣሉ?)

6.5. Do you have any additional comments on this topic?

Thank you for taking the time to conduct this interview with me. Your insights are greatly appreciated, and your perspective has been invaluable in understanding the factors influencing SWC implementation to rehabilitate gullies. We discussed several important issues, and the information you provided will contribute significantly to our research. Once our findings are finalized, we will share the results with you.

Your participation is truly valued, thank you again!

ከእኔ ጋር ይህን ቃል ምልልስ ስላደረጉ በጣም አመሰግናለሁ። ብዙ ጠቃሚ ጉዳዮችን ተወያይተናል የሰጡን መረጃ ለጥናታችን ትልቅ አስተዋፅኦ ይኖረዋል። ግኝቶቻችን እንደተጠናቀቀ ውጤቱን ለእርስዎ እናካፍላለን። በድጋሚ አመሰግናለሁ!

Appendix H: GenAI code of conduct and transparency statement

Student name: Jeanne Vandenbrande Student number:R0906090.....

Please indicate with "X" whether it relates to a course assignment or to the Bachelor's or Master's thesis:

☐ This form is related to a course assignment.

Course name:

Course number:

This form is related to my ☐ Bachelor's or ☒ Master's thesis.

Title Bachelor's or Master's thesis: Mapping and understanding farmers' responses to gully-induced problems in the Abaya-Chamo Sub-Basin, Southern Ethiopia

Supervisor:Dr. Matthias Vanmaercke.....

Daily supervisor: Drs. Yibeltal Mekonnen.....

Please indicate with "X":

☐ I did not use any GenAI assistance tool.

☒ I did use GenAI Assistance. In this case specify which ones (e.g. ChatGPT, M365 Copilot,...): Claude, ChatGPT, Copilot, Google Scholar Labs

GenAI assistance used as/for:	Name of the GenAI tool(s) used. If helpful, also describe in which way you were using GenAI related to what is specified as code of conduct.	Code of conduct:
		For each of the categories below, always take into account the important guidelines and remarks mentioned above (e.g. copyrighted data, sensitive or personal data,...).
As a language assistant for reviewing or improving texts I wrote myself	Claude	This use is similar to using spelling and grammar check tools. In general, you do not have to refer to such kind of GenAI use in the text. However, be careful: - When using GenAI tools on texts you did not write yourself to improve the text, you have to refer to the original source or author , otherwise you are committing plagiarism and thus an irregularity.
As a paraphrasing tool		This use is allowed except when it is prohibited by the teacher or the program of study. You may paraphrase your own text or texts by an author other than yourself and take inspiration from what a GenAI tool or another tool suggests (unless it is not allowed). In general, you do not have to refer to such kind of GenAI use or other paraphrasing tools in the text. However, be careful: - If it entails text by an author other than yourself, you are not allowed to include that paraphrased text without reference to the original source or author . Without such reference, you would be committing plagiarism and thus an irregularity.
For translation aid to improve texts I wrote myself or to better understand text from others	Claude, ChatGPT	This use is allowed except when it is prohibited by the teacher or the program of study. It is similar to using translation tools (Google translate, DeepL, ...). In general, you do not have to refer to such kind of GenAI use in the text.

		However, be careful: - You are not allowed to include that translated text without reference to the original source or author. Without such reference, you would be committing plagiarism and thus an irregularity. - Always check the translated text for correctness and meaning.
As a search engine to get information on a topic or to search for existing research on the topic	Google Scholar Labs	This use is similar to e.g. a Google search or checking Wikipedia. If you write your own text based on this information, you do not have to refer to the use of GenAI in the text. You only have to refer to the existing research and references you have checked and used (without such references you would be committing plagiarism and thus committing an irregularity). However, be careful: - Be aware that the output of the GenAI tool cannot be guaranteed as a 100% reliable source of information. The output may not be entirely correct and/or be limited due to the databases it uses. Moreover, knowledge evolves and may change over time; therefore, the database of the GenAI tool may not be up to date. Therefore, verify the information and do not just copy-paste it as you should understand and critically process everything you are writing.
For literature search	Google Scholar Labs	This use is comparable to e.g. a Google Scholar search. You do not have to refer to such kind of GenAI use; you only have to refer to the literature references you have checked and used (without such references you would be committing plagiarism and thus committing an irregularity).. However, be careful: - Be aware that the search output is restricted to the database the GenAI tool is built on. After this initial search, look for scientific sources and conduct your own analysis of the source documents. Interpret, analyse and process

		the information you obtained; verify it and do not just copy-paste it as you should understand and critically process everything you are writing. - Be aware that some GenAI tools may output no or wrong references. As a student you are responsible for further checking and verifying the absence or correctness of references; do not just copy-paste it.
For generating programming code	Claude, Copilot, ChatGPT	Use of GenAI for coding is allowed except when it is prohibited by the teacher or the program of study. If used for coding, correctly mention the use of GenAI assistance in accordance with the instructions on the page on being transparent about the use of GenAI.
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Other use (specify here; this may also include a combination of types of use mentioned above):		To make sure other use of GenAI is allowed within the course or thesis, and if so, the conditions that may apply, contact the teaching staff of the course or the supervisor of the thesis beforehand and explain the intended GenAI use. Also inform the programme director.
		Motivate how you would comply with Article 84 of the exam regulations. Explain the use and the added value of the AI tool you consider to use and how it is in accordance with the assignment or thesis and the KU Leuven guidelines on responsible use of Generative AI tools. Depending on the kind of GenAI use, it may be needed to properly reference it in the text, in accordance with the instructions page on being transparant about the use of GenAI.