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Drivers of field-saturated soil hydraulic conductivity: Implications for restoring degraded tropical landscapes

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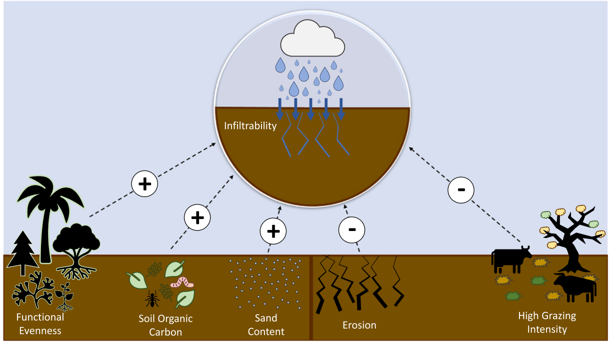
HIGHLIGHTS

- Drivers of infiltrability are identified on the landscape scale.
- High grazing pressure and erosion reduce soil infiltrability.
- Greater soil organic carbon and functional diversity increase soil infiltrability.
- Targeted management interventions can help improve water security.

GRAPHICAL ABSTRACT



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ABSTRACT

Water security represents a major challenge in East Africa, affecting the livelihoods of millions of people and hindering sustainable development. Predicted increases in rainfall intensity and variability are expected to exacerbate water insecurity and land degradation. Improving soil infiltrability is an effective strategy for addressing water insecurity and land degradation. Research on soil infiltrability is often highly localized; therefore, scientific understanding of the drivers of infiltrability on larger spatial scales is limited. The aim of this study was to understand the main drivers of infiltrability across five contrasting landscapes in Kenya. We measured field-saturated hydraulic conductivity (K_{fs}) in 257 plots and collected data for variables representing soil properties (sand content, soil organic carbon (SOC) and pH), land degradation (grazing pressure and presence of erosion), vegetation quantity (woody aboveground biomass), and vegetation quality (functional properties and diversity). We used generalized mixed-effects models to test for the effects of these variables on K_{fs}. Median K_{fs} for the five sites ranged between 23.8 and 101.8 mm h^{-1}. We found that K_{fs} was positively associated with sand content (standardized effect 0.39), SOC content (0.15), and functional diversity of woody vegetation (0.09), while it had a negative relationship with the presence of erosion (−0.24) and grazing pressure (−0.09).

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Subsequently, we conclude that infiltrability can be enhanced through using land restoration strategies which specifically target parameters that affect K_{fs}. The results further support that K_{fs} is not solely dictated by inherent soil properties, and that management interventions which boost SOC, reduce erosion, and minimize unsustainable grazing can help address water scarcity by restoring soil hydrological function.

1. Introduction

Billions of people worldwide suffer from inadequate access to freshwater, a figure that is expected to increase in the coming decades (Liu et al., 2017; Mekonnen and Hoekstra, 2016). Water scarcity limits livelihood opportunities (Falkenmark, 1989) and is one of the main obstacles to sustainable development (Ellison et al., 2017; Mekonnen and Hoekstra, 2016). Freshwater scarcity has become a challenge of global proportions (Falkenmark, 1990). Land degradation exacerbates freshwater scarcity (Bossio et al., 2010) along with a combination of other dynamics such as climate change, more frequent droughts, deforestation, poor land and water management practices, and excessive grazing (Gisladottir and Stocking, 2005; Lal, 1996; Omoro et al., 2011; Vasu et al., 2018; Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services [IPBES], 2018). Combatting land degradation can lead to positive outcomes for biodiversity, water and food security, employment, gender equality, and conflict avoidance (IPBES, 2018). Land degradation affects 3.2 billion people worldwide, with tropical drylands being particularly vulnerable (IPBES, 2018). Soil erosion represents one of the most significant processes that contribute to land degradation, resulting in reduced soil organic carbon (SOC) and diminished infiltrability (Bruijnzeel, 2004; Nyberg et al., 2012), thus negatively impacting water security. These processes reduce soil water retention and increase surface runoff, further exacerbating erosion (Lal, 1996; Lal and Shukla, 2004). East Africa is predicted to undergo an increase in the intensity and frequency of heavy precipitation events due to global climate change (Intergovernmental Panel on Climate Change [IPCC], 2022), with an expected 30 % increase in precipitation during the short rain season by the mid-21st century (Cook et al., 2020). In soils with low infiltrability, heavier rainfall could lead to increased surface runoff, elevating the risk of erosion and flooding. These consequences ultimately jeopardize land health, food, and water security (Bargués-Tobella et al., 2019; Mahé et al., 2010), accentuating the urgent need to restore degraded land to adapt to climate change.

Improving soil hydrological function, particularly soil infiltrability, is key to increasing water and food security (Malmer et al., 2010) and should be central to restoration efforts. Soil infiltrability is defined as "the flux which the soil profile can absorb through its surface when it is maintained in contact with water at atmospheric pressure" (Hillel, 1971), and enhancing it can play an important role in addressing freshwater scarcity by increasing soil water recharge and, eventually, groundwater recharge (Hillel, 1971; Bonell, 1993; García-Gutiérrez et al., 2018; Ilstedt et al., 2007; Y. Liu et al., 2019). In tropical drylands, rainfall characteristics (high intensity, few events, and a high spatio-temporal heterogeneity), combined with soils that have a low infiltrability, limit productivity and represent a challenge for food security (Eckholm, 1976; Falkenmark, 1989; Rockström et al., 2010). A better understanding of the infiltration process, including how it relates to soil properties and is influenced by biophysical and anthropogenic factors, is essential for effective soil and water management (Hillel, 1971).

Existing research recognizes the critical role of inherent soil properties such as particle size distribution on soil infiltrability. Coarse-textured soils typically have larger pores than more fine-textured soils, and therefore have a greater hydraulic conductivity (Blackburn, 1975; Hillel, 1980; García-Gutiérrez et al., 2018; Mongil-Manso et al., 2021; van Schaik, 2009). Another inherent soil property that may affect soil infiltrability is pH, which influences clay dispersibility and can contribute to the degradation of soil physical properties (Chorom et al., 1994; Mills et al., 2006). Soils dominated by more active, swelling clay minerals are more dispersive and tend to have lower hydraulic conductivity when saturated (Lado and Ben-Hur, 2004; Lehmann et al., 2021). Higher pH values in dryland soils could be indicative of the predominance of more active and dispersive clays and subsequently lower soil infiltrability (Mills et al., 2006). SOC, which is a key indicator of soil health (Lal, 2016), has been found to enhance soil infiltrability (Franzluebbers, 2002; Hassler et al., 2011; Lozano-Baez et al., 2019; Mills et al., 2006; Mongil-Manso et al., 2021), mainly through improved soil structure and aggregation (Faucon et al., 2017; Franzluebbers, 2002; Hao et al., 2020; Lado et al., 2004). Land use typically affects infiltration through concurrent impacts on soil structure, organic matter inputs, and vegetation cover. Heavy livestock grazing can reduce infiltrability through soil compaction, leading to the loss of soil physical structure and porosity (Lulandala et al., 2021; Savadogo et al., 2007). Converting forests to cropland can result in large-scale depletion of SOC and subsequent reduced infiltrability (Nyberg et al., 2012). In the tropics, managing the hydrological function of soil also relies on understanding the effect of woody vegetation on infiltrability.

Woody vegetation can increase soil infiltrability through enhanced macroporosity resulting from root and faunal activity, and through increased above- and belowground litter inputs, which contribute to improved soil structure and aggregation (Bargués-Tobella et al., 2019; Bargués Tobella et al., 2014; Bonnesoeur et al., 2019; Ilstedt et al., 2007; Kuyah et al., 2016; Léonard et al., 2004; Mando et al., 1996; Van Schaik et al., 2014; van Schaik, 2009). Although several studies have shown positive links between woody vegetation and infiltrability (Benegas et al., 2014; Ilstedt et al., 2007; Mongil-Manso et al., 2021; Mens et al., 2023), the strength of these effects depends on vegetation type and the interplay between different factors relating to soil properties (Hao et al., 2020) and climatic conditions (Thompson et al., 2010). The effect of aboveground woody biomass on infiltrability therefore remains poorly understood. The effects of woody vegetation quality, such as tree species and diversity, are even less understood (Chandler et al., 2018; Ilstedt et al., 2007; Malmer et al., 2010; Sanou et al., 2010). Designing effective restoration measures involves understanding the effect of woody vegetation in terms of both its quantity and its quality.

A growing body of literature recognizes that ecosystem function is better reflected by the functional traits of species and functional diversity (FD) of communities than by simply identifying which species are present (Botta-Dukát, 2005; Cadotte et al., 2009; Díaz and Cabido, 2001; Fischer et al., 2018; Zhu et al., 2015). For example, species-specific resource-use strategies such as specific leaf area (SLA) affect soil properties by increasing the input of organic matter, altering the abundance of macrofauna, and affecting decomposition rates (De Deyn et al., 2008; Loranger-Merciris et al., 2007; Pérez-Harguindeguy et al., 2013). The diversity of traits in an ecosystem can also affect overall resource-use efficiency (Cardinale et al., 2006; Chapin et al., 1997; Hodapp et al., 2019; Loreau et al., 2001). Hence, FD can influence SOC (Prommer et al., 2020) and increase the diversity of macrofauna (Schuldt et al., 2020). More research is needed to understand how the functional properties of woody vegetation affect soil properties such as infiltrability (Faucon et al., 2017; Mens et al., 2023), and to produce evidence for which tree-based restoration initiatives can promote more desirable species (Lohbeck et al., 2017). A recent study found that functional traits in fast-growing woody species which relate to acquisitive resource-use, such as a high SLA and deciduousness, positively influence infiltrability (Mens et al., 2023). Trees with an acquisitive strategy are also linked to increased carbon sequestration, soil macrofauna abundance, and microbial activity (Mens et al., 2023; Frouz et al.,

2013) – factors that positively influence SOC content. In one landscape in Kenya, Mens et al. (2023) found that woody biomass, lower leaf thickness and toughness (high SLA), and higher species richness had positive effects on infiltrability through an associated increased in macrofaunal abundance. In contrast, species with a high wood moisture content negatively affected SOC, which is strongly related to infiltrability (Mens et al., 2023).

Previous studies have established that there is a relationship between infiltrability and varying biophysical conditions (Demand et al., 2019; Ilstedt et al., 2007; Lulandala et al., 2021) and between woody vegetation quality and infiltrability (Mens et al., 2023, Frouz et al., 2013). To date, however, few studies have investigated the drivers of soil infiltrability at larger spatial scales, primarily because these measurements are both cost- and time-intensive (Demand et al., 2019; Ilstedt et al., 2007; Lulandala et al., 2021). There therefore remains a great need to study these drivers across contrasting and diverse landscapes and apply these insights to land restoration practices (Demenois et al., 2018; Hao et al., 2020; Zhu et al., 2015).

This study aims to assess key factors that drive field-saturated soil hydraulic conductivity (K_{fs}) across five contrasting landscapes in Kenya. K_{fs} is the measurement of soil hydraulic conductivity in the field when the soil matrix is saturated and is assumed to be equivalent to the soil steady-state infiltrability (Hillel, 1971). We chose K_{fs} as it is a key soil hydraulic property that influences soil infiltrability and because it is independent of the initial soil water content, which allows for comparison of the infiltrability of soils with differences in initial soil moisture content (Hillel, 1971). We used a dataset consisting of soil and land health data collected systematically across the five sites using the Land Degradation Surveillance Framework (LDSF) (Vågen et al., 2010). The specific objectives were to characterize the sites, and test for the effects of soil properties, land degradation, and quantity and quality of vegetation on K_{fs}. Our initial hypotheses were that soil sand content, SOC, woody vegetation quantity, and functional diversity of woody vegetation would have a positive effect on K_{fs}, whereas erosion, grazing pressure, and pH would have a negative effect.

2. Materials and methods

2.1. Study sites

Data was gathered from five 100 km^2 sites in Kenya: Chasimba (Kilifi county), Gatunga (Tharaka-Nithi county), Muminji (Embu county), Thange (Makueni county), and Kubo South (Kwale county) (Fig. 1). Land use varies both between and within sites, with cropland and grazing land being dominant. Smallholder farmers cultivate a variety of crops such as maize (*Zea mays* L.), cowpea (*Vigna unguicolata* L.), green grams (*Vigna radiata* L.), cashew (*Anacardium occidentale* L.) and khat (*Catha edulis* Vahl.). In total, 257 plots were surveyed, of which 159 (62 %) were under cultivation, and the remaining 98 (38 %) were not. Nearly all plots (98 %) were privately owned. The sites experience contrasting climates and represent a gradient in aridity and precipitation (Table 1).

2.2. Soil and land health field survey

The sites were sampled following the Land Degradation Surveillance Framework (LDSF) methodology, as part of the Kenya Cereals Enhancement Programme – Climate Resilient Agricultural Livelihoods Window (KCEP-CRAL) project in 2018–2019. The LDSF consists of a hierarchical field survey and sampling design based on sites that are 100 km^2 (10 × 10 km) in size (Fig. 1). Each site is divided into 16 tiles (2.5 km × 2.5 km). Centroid locations for clusters are randomized within each tile. Each cluster is 1 km^2 in size and contains 10 plots, with randomized center-points pinned out within a 564 m radius from the cluster's centroid. Each individual plot is 1000 m^2 and contains 4 subplots 100 m^2 in size. Thus, the methodology results in a spatially stratified randomized sampling design that minimizes local biases. For the current study, a subset of LDSF plots with soil infiltration measurements was used, with three plots sampled per cluster in each site in Chasimba (n = 48), Gatunga (n = 41), Kubo South (n = 42), and Thange (n = 42). In Muminji, five plots were sampled in each cluster (n = 84). A total of 257 plots were surveyed across all sites. In each plot, we measured variables related to vegetation structure, the quantity of woody

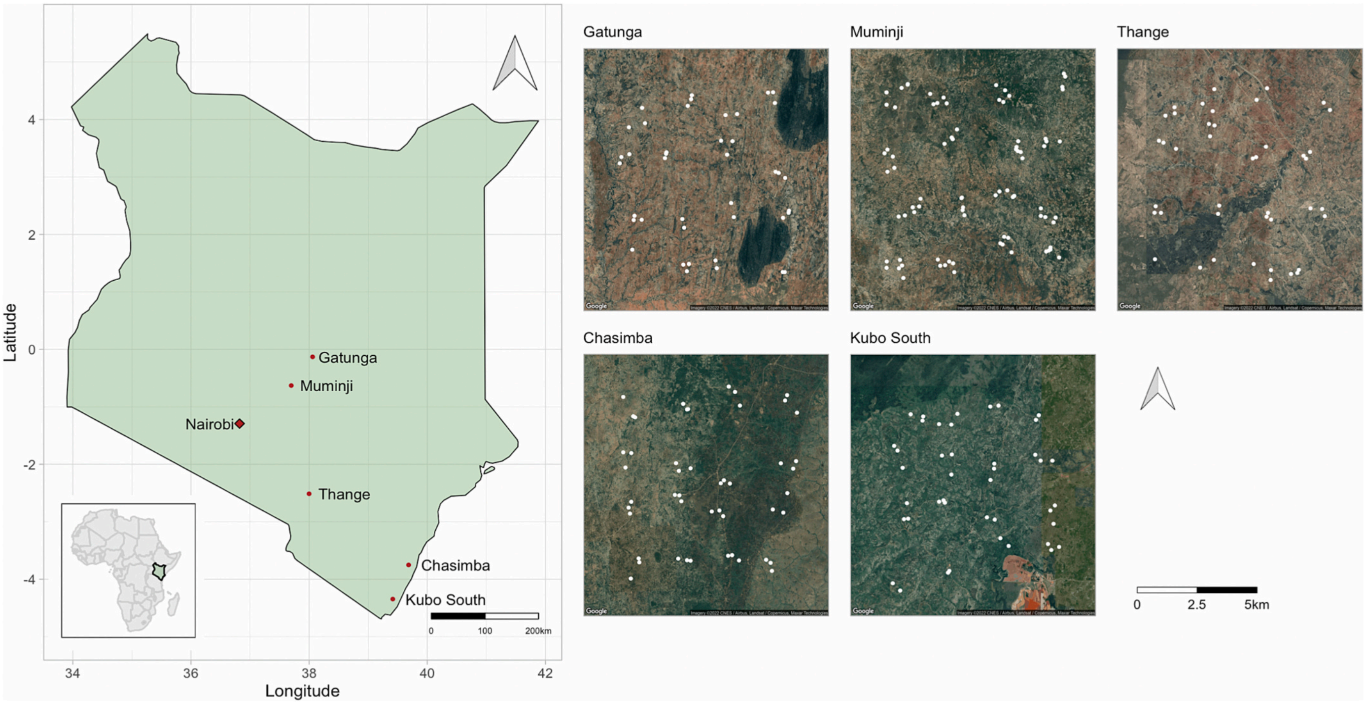

Fig. 1. Map of Kenya showing the locations of the five study sites, each site being 10 × 10 km. The white dots in the site map indicate the location of the sampling plots. The site maps were produced using the ggmap package (Kahle and Wickham, 2013).

Table 1

Climatological and descriptive data for all five study sites. Sites included in the study, indicating their location (latitude and longitude range), average annual aridity index (AI = mean annual P/mean annual PET) over the period 1970–2000 (Trabucco and Zomer, 2018) and corresponding aridity class based on the United Nations Environment Programme's (UNEP) classification system (UNEP, 1997), the Köppen-Geiger climatic zone (Kottek et al., 2006), average annual precipitation for the period 1970–2000 (Fick and Hijmans, 2017), and average elevation. Individual plot values within each site were used to derive the average values for each site.

Site	Latitude range	Longitude range	Aridity class	Average aridity index	Köppen-Geiger climatic zone	Average mean annual precipitation (mm)	Average elevation (m)
Chasimba	−3.7108300–−3.79180	39.6470–39.7247	Humid	0.66	Equatorial savannah with dry summer (As)	1077.9	165.8
Gatunga	−0.0939892–−0.169166	38.0202–38.0959	Semi-arid	0.23	Equatorial savannah with dry winter (Aw)	565.1	601.2
Kubo South	−4.3128500–−4.390170	39.3801–39.4545	Humid	0.80	Equatorial savannah with dry summer (As)	1255.6	90.1
Muminji	−0.5855520–−0.670992	37.6580–39.7388	Dry sub-humid	0.54	Equatorial savannah with dry winter (Aw)	922.9	1119.2
Thange	−2.4751400–−2.555210	37.9613–38.0397	Semi-arid	0.33	Equatorial savannah with dry winter (Aw)	609.8	919.9

vegetation, soil infiltration, erosion, grazing, and inherent and dynamic soil properties.

Data concerning vegetation structure was collected at the plot level (1000 m^2). Plots were classified using the Food and Agriculture Organization's (FAO) Land Cover Classification System (LCCS) based on White (1983), which divides the predominant vegetation structure into the following categories (Di Gregorio and Jansen, 1998): bushland, cropland, grassland, shrubland, and wooded grassland (Table A.1).

Within each subplot (100 m^2), all woody plants over 1.5 m in height were identified and measured. Tree measurements included height and circumference at breast height (>3 m height), and shrub measurements included height, width, and length for shrubs (1.5–3 m height). Where accurate species identification was not possible, woody plants were identified to the genus level or local species names were recorded.

Soil infiltration was measured at the center of each plot using a single-ring infiltrometer (Bouwer, 1986), as these are more time-efficient and use less water than double-ring infiltrometers, allowing for repeated measurements across different plots. A single-ring infiltrometer with an inner diameter of 15.6 cm and height of 20 cm was placed in the center of the plot (which coincides with the center of subplot 1) and carefully inserted into the soil to minimize disturbance of the soil surface. The soil inside the infiltrometer was pre-wetted by slowly pouring water into the infiltrometer to avoid soil surface disturbance. Infiltration measurements were initiated after 15 min of pre-wetting. An upright ruler was fixed to the inside of the infiltrometer. During the first 30 min of the infiltration experiment, the water level was recorded at 5-minute intervals. After recording the water level, the infiltrometer was immediately refilled to the initial starting level. The time interval was increased to 10 min during the subsequent 60 min and was increased again to 20 min during the remaining infiltrability measurement period which lasted for 2.5 h overall to ensure that steady-state conditions were attained.

Topsoil (0–20 cm) samples were collected using an auger at the center of each subplot. In each plot, the four samples were pooled into a composite plot-level topsoil sample. Within subplot 1, visible signs of erosion were recorded and classified into three erosion types: sheet, rill, and gully. Each plot was assigned a binary classification of 0 or 1 based on the presence or absence of erosion.

The impact of grazing on habitat was visually assessed at the plot level using a score of 0 (no impact) to 3 (severe impact). Although this scoring involved an inherent element of subjectivity, the assessment was conducted by the same team within each site, meaning that the variation across plots was deemed sufficiently robust for analysis (Lohbeck et al., 2020).

2.3. Soil laboratory analyses

Soil samples were initially air-dried and then ground to pass through a 2 mm-sieve. A subset (10 %) of the soil samples was analyzed for pH, texture, and organic carbon using standard analytical methods. Soil pH was measured using a Eutech Cyberscan 1100 pH meter [Eutech Instruments Pte. Ltd.] at Crop Nutrition Laboratory Services in Nairobi, Kenya. Soil pH was analyzed in a solution obtained by mixing 20 g of soil with 40 mL of de-ionized water. The solution was shaken for 30 min and then kept stationary for 20 min prior to pH analysis. Soil organic carbon (SOC) was measured using dry combustion with an Elemental Analyzer Isotope Ratio Mass Spectrometry (EA-IRMS) [Europa Scientific Ltd.] at the IsoAnalytical Laboratory, United Kingdom. Inorganic carbon was removed prior to the measurement of SOC using 0.1 N HCl. Sand content was measured using a LA-950 Laser Diffraction Particle Size Analyzer (LDPSA) [HORIBA Ltd.] at the ICRAF Soil–Plant Spectral Diagnostics Laboratory in Nairobi, Kenya. Each soil sample was shaken for 4 min in a 1 % sodium hexametaphosphate (calgon) solution before being analyzed.

All soil samples were analyzed for mid-infrared (MIR) absorbance using the Tensor 27 HTS-XT [Bruker Optics] at the ICRAF Soil–Plant Spectral Diagnostics Laboratory in Nairobi, Kenya. The MIR spectra were processed using the methodology described in Terhoeven-Urselmans et al. (2010). Reference soil samples with both standard analytical data and MIR spectra were used to develop random forest regression models (Breiman, 2001), to simultaneously predict the different soil properties (soil texture, SOC, pH) for the remaining 90 % of samples with MIR spectra only (Vågen et al., 2016). Reference samples used to build random forest models included not only the samples collected in this study, but also those in the ICRAF pan-African MIR spectral library. In total, 12,502 reference samples were used for model development and testing.

2.4. Aboveground woody biomass (vegetation quantity)

The sum of the woody biomass of both trees and shrubs in each subplot was calculated using allometric equations. The average biomass across the four subplots was used to derive a plot-level aboveground woody biomass (AGB) expressed in megagrams per hectare. A singular best-fit pan-tropical allometric equation (Chave et al., 2014) was used to calculate AGB for all tree species except for *Adansonia digitata* L. The formula in Chave et al. (2014) was based on diameter at breast height (cm), tree height (m), and wood density (g cm^{-3}) (WD). The formula in Conti et al. (2013) was used to estimate aboveground biomass for shrubs based on height (cm), crown area (cm^2), and WD. The pan-tropical allometric equations were not suitable for estimating the AGB of *A. digitata* L. due to the unique morphology of these trees, which have low WD and are often hollow. Therefore, a species-specific equation was applied for AGB estimations of *A. digitata* L (Malimbwi et al., 2016). A site-averaged value for WD was used for 12 species that were identified using only their local names.

2.5. Functional properties of the woody vegetation (vegetation quality)

Four functional traits were used as indicators of species resource-use strategies: WD, specific leaf area (SLA), deciduousness (0/1), and the ability to fix nitrogen (0/1). Traits were collected locally in one of the five landscapes (Muminji; Mens et al., 2023) or sourced from public databases. Trait data covered 315 species that were found across the five study landscapes. 82 of the 315 species were identified only at the genus level. Information on deciduousness and wood density could not be found for 4 % and 1 % of species, respectively.

Local data was prioritized and used for 11 % of species for WD and 13 % of species for SLA, deciduousness, and nitrogen fixation (Mens et al., 2023). Additional WD values were sourced from a variety of databases, such as Zanne et al. (2009) (Table A.2). Values for SLA (mm^2 mg^{-1}) were also obtained from the TRY Plant Trait Database (Kattge et al., 2020) (Table A.2). To limit the influence of extreme values for SLA and WD, when several values were available a median was derived for each species. In the absence of species-specific data, a genus or family-level median was used (Table A.3).

Species were classified as evergreen (0) or deciduous (1) based on the literature (Maundu and Tengnäs, 2005; Iversen et al., 2017; Kattge et al., 2020) (Table A.2). Out of 315 woody species, 291 were classified (92 %) at the species or genus level. In cases of conflicting information, the most frequently occurring classification was used.

Species' nitrogen fixation ability was derived from the literature and given a binary score expressing their ability to fix nitrogen (1) or not (0) (Table A.2). Species belonging to the Leguminosae family were assumed to be nitrogen-fixing (Soltis et al., 1995) and non-legumes were assumed to be non-nitrogen-fixing unless specific data in the literature stated otherwise. For the12 species identified by their local names, we used the median SLA and WD, and the most common mode of deciduousness and nitrogen-fixation across all species in the study.

Based on the four functional traits, functional diversity (FD) and community-weighted means (CWM) were calculated at the plot-level using the FD package in R (Laliberté et al., 2014). Both were weighted by species' relative abundances in each plot by summing total abundance of trees and shrubs across subplots. CWMs were calculated for each trait separately (CWM SLA, CWM WD, CWM NFix, CWM Decid). CWM SLA, and CWM WD were computed as continuous variables as the data recorded for the traits was continuous (cm^2 g^{-1} and g cm^{-3}). Deciduousness and nitrogen fixation were recorded as factor variables and then converted to continuous variables when calculating CWMs, based on a scale of 0 to 1. For CWM Decid, a value of 0 represented no deciduous woody species in a plot, and 1 indicated a plot fully dominated by deciduous trees. A value of 0.5 indicated an even split between evergreen and deciduous woody species. For CWM Nfix, 0 described a plot with no nitrogen-fixing woody species, and a value of 1 indicated that the plot contained only nitrogen-fixing woody species.

The following FD indices were calculated: functional evenness (FEve) (Villéger et al., 2008), functional divergence (FDiv) (Mason et al., 2005), functional species richness (FSpRi) (Laliberté and Legendre, 2010), functional richness (FRic) (Villéger et al., 2008), functional dispersion (FDis) (Laliberté and Legendre, 2010), and Rao's Quadratic Entropy (RaoQ) (Botta-Dukát, 2005). FEve represents the evenness in species abundance distribution within the functional trait space of a community and reflects the under- or overutilization of resources (Mason et al., 2005). FEve also describes whether the functional traits are distributed regularly in the functional trait space based on species abundances. FDiv indicates niche differentiation by measuring how species abundance is partitioned on the functional trait axis of a community (Mason et al., 2005). FSpRi is a quantitative measure of the number of functionally distinct species in a community (Laliberté and Legendre, 2010). FRic is related to the quantity of different species and signifies the amount of functional space species occupy (Villéger et al., 2008). FDis describes the mean distance of individual species from the centroid of the total functional traits in a community (Laliberté and Legendre, 2010). Lastly, like FDis, RaoQ measures how species are distributed in the functional trait space. Rather than comparing species based on the centroid, it measures the mean distance between two randomly selected species in a community (Botta-Dukát, 2005; Laliberté and Legendre, 2010). A value of 0 was assigned to a plot when it contained no woody vegetation in any of the subplots, or when the minimum number of functionally distinct species for FD was not attained. FDis and RaoQ required ≥ 2 functionally distinct species to be computed, FEve and FDiv required ≥ 3, and FRic required ≥ 4. 90 plots had either 0 or 1 functional species (35 %), 24 had 2 functionally distinct species (9 %), 26 had 3 functionally distinct species (10 %), and the remaining 117 plots had ≥ 4 functionally distinct species (46 %).

2.6. Field-saturated hydraulic conductivity

The analytical formula proposed by Nimmo et al. (2009) was used to calculate field-saturated soil hydraulic conductivity (K_{fs}) (Reynolds and Elrick, 1990) from the field infiltration measurements. This formula corrects for hydrostatic pressure, non-constant falling head, and subsurface lateral spreading effects. For each infiltration measurement from each plot, an asymptotic function was fitted to its corrected infiltration curve. The asymptote, which represents K_{fs}, was derived using the *nls.multstart* package in R (Padfield and Matheson, 2018).

2.7. Statistical analysis

The plot is our unit of replication ($N = 257$). We fitted a generalized linear mixed model (GLMM) with a gamma distribution and log link function to examine the effect of different variables on K_{fs} (Bates et al., 2015). This was deemed the most appropriate modelling approach due to the nested nature of the LDSF data, the need to account for variation in K_{fs} between and within sites, and the skewed, positive, and continuous nature of K_{fs}. The glmmTMB() function in the *glmmTMB* package (Brooks et al., 2017) was used to fit random intercept GLMMs. We followed the protocol for mixed modelling proposed by Zuur et al. (2013). First, a series of candidate models was constructed to test the effect of the covariates in the fixed part of the model on K_{fs}. Explanatory variables for inherent soil properties (sand content and pH), dynamic soil properties (SOC), land degradation (erosion presence and grazing impact), vegetation quality (FEve, FSpRi, FDiv, FDis, FRic, RaoQ, CWM SLA, CWM WD, CWM NFix, CWM Decid), and vegetation quantity (woody AGB and vegetation structure) were used as fixed effects. Sites and clusters within sites were used as random effects. The fixed effects were standardized using the *MyStd()* function in the *regularizedSCA* package (Gu and Van Deun, 2018).

Twenty alternative models were constructed with the same number of variables containing different combinations of covariates (Table A.4). The base model contained sand content, pH, erosion presence/absence, grazing impact, and SOC. Two more covariates were added to the base model, representing vegetation quality (10 variables) and quantity (2 variables), making a total of 20 alternative models. All variables were included as interaction terms with sand content, as the effect of the different variables was expected to change depending on soil texture.

The 20 candidate models were compared using Akaike Information Criterion (AIC) (Burnham and Anderson, 2002) derived using the anova() function in the *stats* package (R Core Team, 2022). The model with the lowest AIC score was selected as the optimal model (Burnham and Anderson, 2002) (Table A.4). We applied a limited amount of variable selection to the optimal model, dropping only non-significant interaction terms. This was done using the *drop1()* function in the *stats* package based on a likelihood-ratio test (Bates et al., 2015).

We followed the model validation steps described in Zuur et al. (2013) to rule out any indication of model misspecification, including the violation of homogeneity assumptions and the presence of non-linear patterns or spatial dependencies. We also checked the models for collinearity using the function *check_collinearity()* from the *performance* package (Lüdecke et al., 2021), which uses the variance inflation factor. Collinear variables were excluded from the same model (Harrison et al., 2018) to avoid increasing standard error and to simplify assessment of the independent effect of the predictors on the response variable (Quinn and Keough, 2002; Harrison et al., 2018).

The significance of fixed effects in the final optimal model was evaluated based on *t*-tests using the Satterthwaite approximation for degrees of freedom (Kuznetsova et al., 2017). A significance level (α) of 0.05 was used. The Satterthwaite method for deriving p-values is suitable for smaller and unbalanced datasets as it results in lower Type 1 error rates as compared to likelihood ratio tests and Wald tests (Luke, 2017). The *performance* package was used to derive R^2_{marginal} and $R^2_{\text{conditional}}$ values for fixed effects (Nakagawa and Schielzeth, 2013). All statistical analyses were conducted using R statistics (R Core Team, 2022).

3. Results

3.1. Site characterization

Results from the field surveys indicate stark differences between sites in terms of soil properties, vegetation quantity and quality, and land degradation status.

Median K_{fs} was highest in Kubo South, followed by Chasimba, Muminji, Thange and Gatunga, where the median values were less than half of that in Kubo South (Fig. 2A, Table A.5). Among the sites, K_{fs} varied more than other soil properties did, with median K_{fs} being four times higher in Kubo South than in Gatunga. Furthermore, within-site variation was greater in sites with higher median K_{fs} than those with lower K_{fs} values. Median K_{fs} was greatest in plots where the vegetation structure was classified as bushland (56.2 mm h^{-1}), followed by wooded grassland (46.5 mm h^{-1}), shrubland (41.7 mm h^{-1}), cropland (39.7 mm h-^{1}), and grassland (21.6 mm h^{-1}) (Fig. 2B).

Soils in Kubo South exhibited both the highest median sand content (59.0 %) and the lowest SOC (5.27 g C kg^{-1}) (Fig. 3A and B). In contrast,

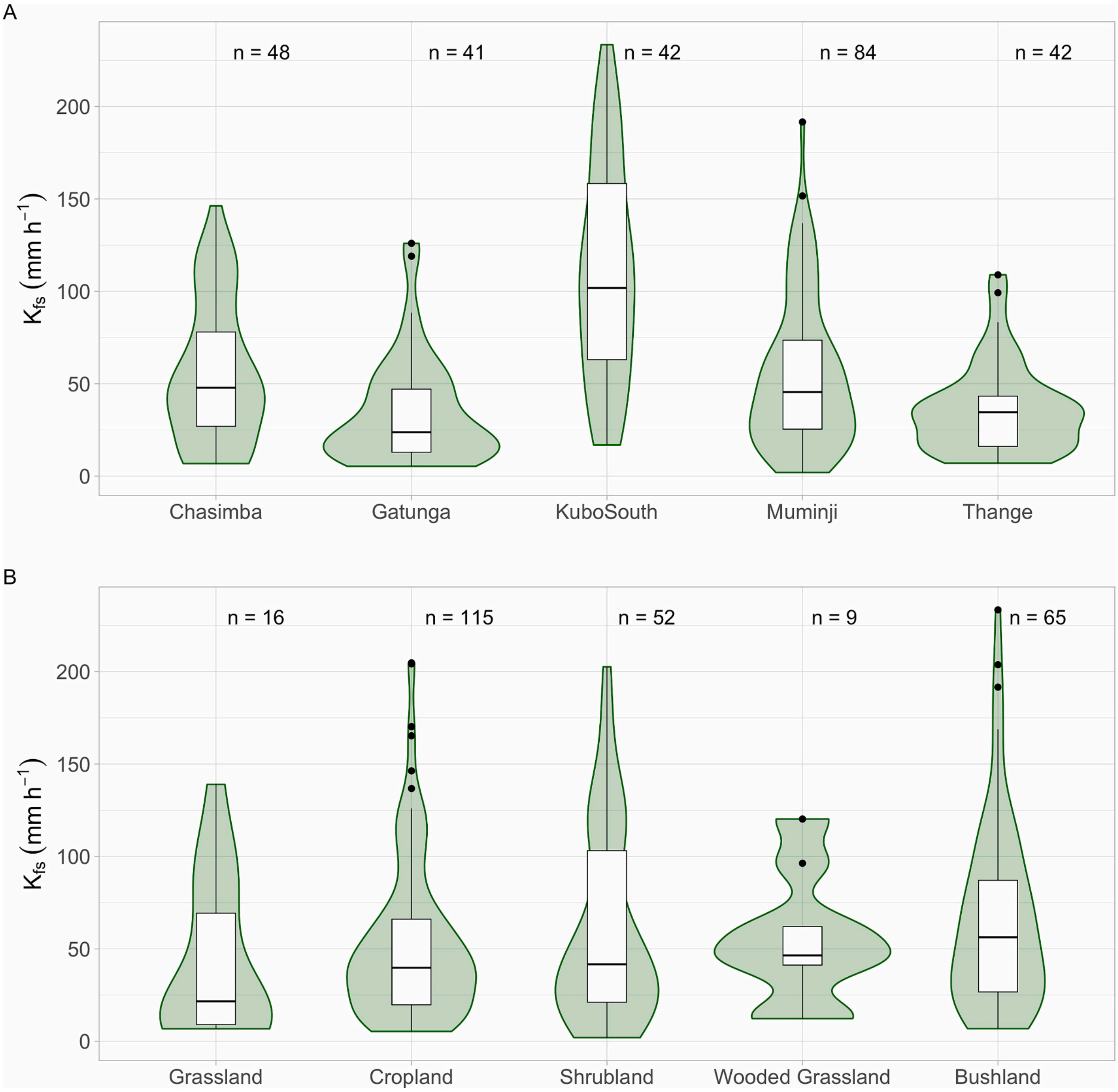

Fig. 2. Violin and boxplots (lower quartile, median and upper quartile) showing the variation in topsoil field-saturated hydraulic conductivity between and within (A) sites and (B) vegetation structure classes across the five study sites in Kenya. The number of observations per site (n) is indicated above plot (A). The number of observations per vegetation structure class (n) is indicated above plot (B).

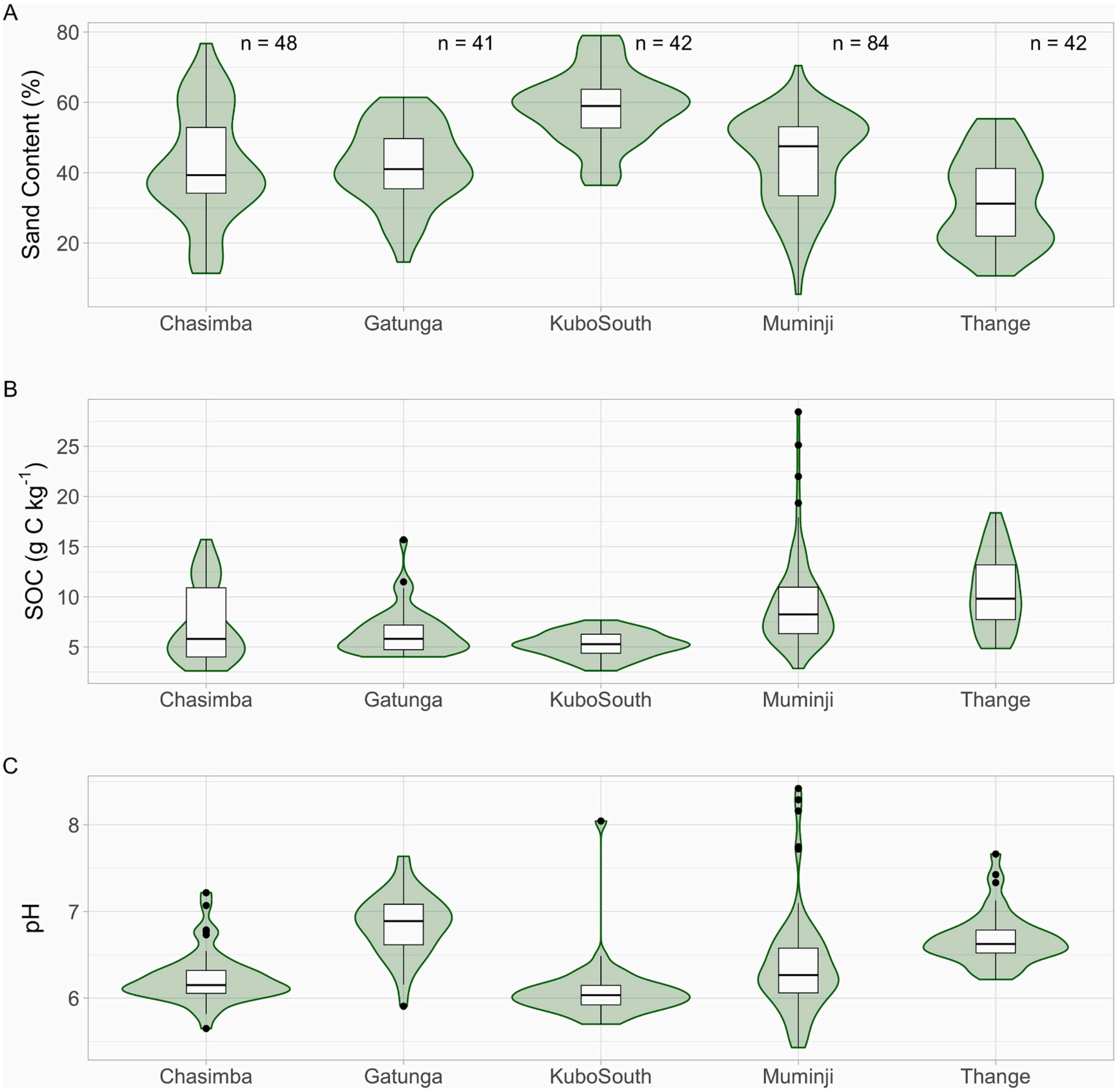

Fig. 3. Violin and boxplots (lower quartile, median and upper quartile) showing the variation in (A) sand content, (B) soil organic carbon (SOC) and (C) pH across and within plots in the five study sites in Kenya. The number of observations per site (n) is indicated above the top panel.

Thange had the lowest median sand content (31.2 %) and the highest median SOC (9.81 g C kg^{-1}). The median pH for each site was less variable and ranged from 6.03 in Kubo South to 6.89 in Gatunga (Fig. 3C). Median pH was lower in the more humid sites (Kubo South, Chasimba, Muminji) than in the drier sites (Thange and Gatunga) (Table A.5).

Median woody AGB was highest in Kubo South, followed by Chasimba, Muminji, Thange, and Gatunga (Fig. 4A, Table A.5). Cropland was the dominant vegetation structure class across the sites, accounting for nearly half (45 %) of all plots (Fig. 4B). Chasimba had the highest proportion of cropland, followed by Thange, Gatunga, Kubo South, and Muminji (Table A.6). Muminji was the only site where cropland was the second most dominant vegetation structure class after bushland. The least occurring vegetation classes across all sites were grassland (6.2 %) and wooded grassland (3.5 %).

Kubo South had not only the highest woody biomass but also the highest functional diversity, as indicated by larger median values for all FD indices (Fig. 5, Table A.5). Chasimba, Gatunga and Thange all had more negatively skewed distributions of vegetation quality values, with median values of 0 for FEve, FDiv and FRic (Fig. 5A, B & F). The high number of plots containing few functionally distinct species (i.e., 0 diversity), resulted in a negatively skewed distribution of the FD indices.

The contrast between sites was smaller for the community-weighted means of specific leaf area (CWM SLA) and wood density (CWM WD) than for the FD indices. Kubo South had the highest median CWM SLA, followed by Chasimba and Thange (Fig. 5G, Table A.5). The median CWM WD values for all sites were very similar and ranged from 0.54 g cm^{-3} (Chasimba) to 0.65 cm^{-3} (Muminji) (Fig. 5I). The CWM SLA and CWM WD for Chasimba and Gatunga were negatively skewed. All sites were dominated by species without the capacity for nitrogen fixation. The highest proportion of nitrogen-fixing species was in Gatunga and Thange, while nitrogen-fixing species were completely absent in Chasimba (Fig. 5H). The CWM for deciduousness indicates that all sites were dominated by evergreen species, with the highest proportion in Chasimba and Muminji, and the lowest in Thange (Fig. 5J).

More than half of the plots in Chasimba, Gatunga and Muminji showed visible signs of erosion. In contrast, only 9.5 % of plots in Kubo South and 33.3 % in Thange showed signs of erosion (Fig. 6A). Gatunga had the highest percentage of plots displaying signs of severe grazing impact (31.7 %), followed by Thange (9.52 %) and Chasimba (6.25 %), while Kubo South had no plots with signs of severe grazing (Fig. 6B). Chasimba was the site with the highest percentage of plots with no signs of grazing (66.6 %).

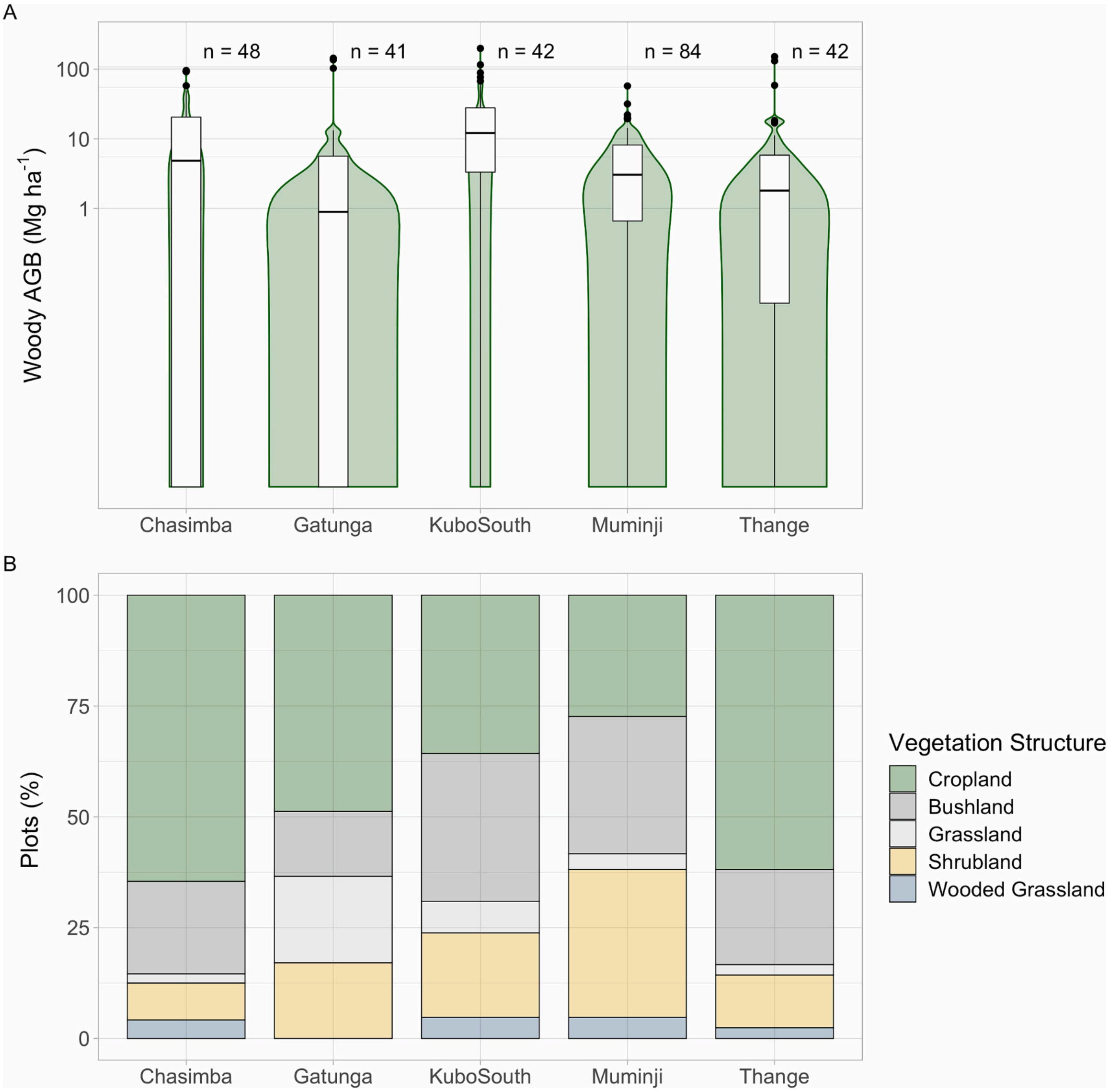

Fig. 4. Violin and boxplots (lower quartile, median, upper quartile) and percentage bar chart illustrating the variation in (A) woody aboveground biomass (AGB) and (B) vegetation structure classes across and within plots in the five study sites in Kenya. The y-axis of B has been log-scaled to improve readability. The number of observations per site (n) is indicated above the top panel.

3.2. Optimal explanatory model

Results from the GLMM model show that sand content had the greatest effect on K_{fs}, followed by the presence of erosion and SOC (Table 2, Fig. 7). Our model indicates a significant positive effect of sand content ($p < 0.001$) and SOC ($p = 0.022$) on K_{fs} (Table 2, Fig. 8A & C). In contrast, erosion had a significant ($p = 0.019$) negative effect on K_{fs}, with plots containing visible signs of erosion exhibiting lower K_{fs} than those without such signs (Fig. 8H). Erosion had an almost significant interaction effect with sand content ($p = 0.057$), suggesting that the positive effect of sand content on K_{fs} was reduced in plots affected by erosion (Fig. 8I).

Grazing impact had a slight, but not statistically significant ($p = 0.083$) negative effect on K_{fs} (Fig. 8F). However, there was a significant ($p = 0.022$) interaction effect between sand content and impact of grazing, indicating that the negative effect of grazing impact on K_{fs} was less pronounced for sandy soils than for more fine-textured soils (Fig. 8G). Functional evenness (FEve) of woody vegetation had a positive effect on K_{fs}, although this was not statistically significant in this study ($p = 0.068$; Fig. 8E). pH ($p = 0.711$) and woody AGB ($p = 0.512$) were not statistically significant in the final model (Table 2).

4. Discussion

Our results indicate that the most important predictors in explaining variation in K_{fs} across the five sites were: soil sand content, SOC, impact of grazing, and presence of erosion were (Table 2). Although sand content is an inherent soil property and cannot be altered through management, SOC, erosion, and grazing can. The effect of SOC on K_{fs} was positive (Fig. 8C), suggesting that restoration measures focusing on increasing SOC content may be an effective way of enhancing K_{fs} and soil hydrological function. Both the impact of grazing and the presence of erosion negatively affected K_{fs} (Fig. 8F & H), which indicates that limiting the impacts of grazing and the spread of erosion, through targeted management and land use practices, could be efficient strategies for restoring K_{fs}. The effects of vegetation quantity and quality were minor (Fig. 8D & E). These results are discussed in the context of land restoration in degraded landscapes.

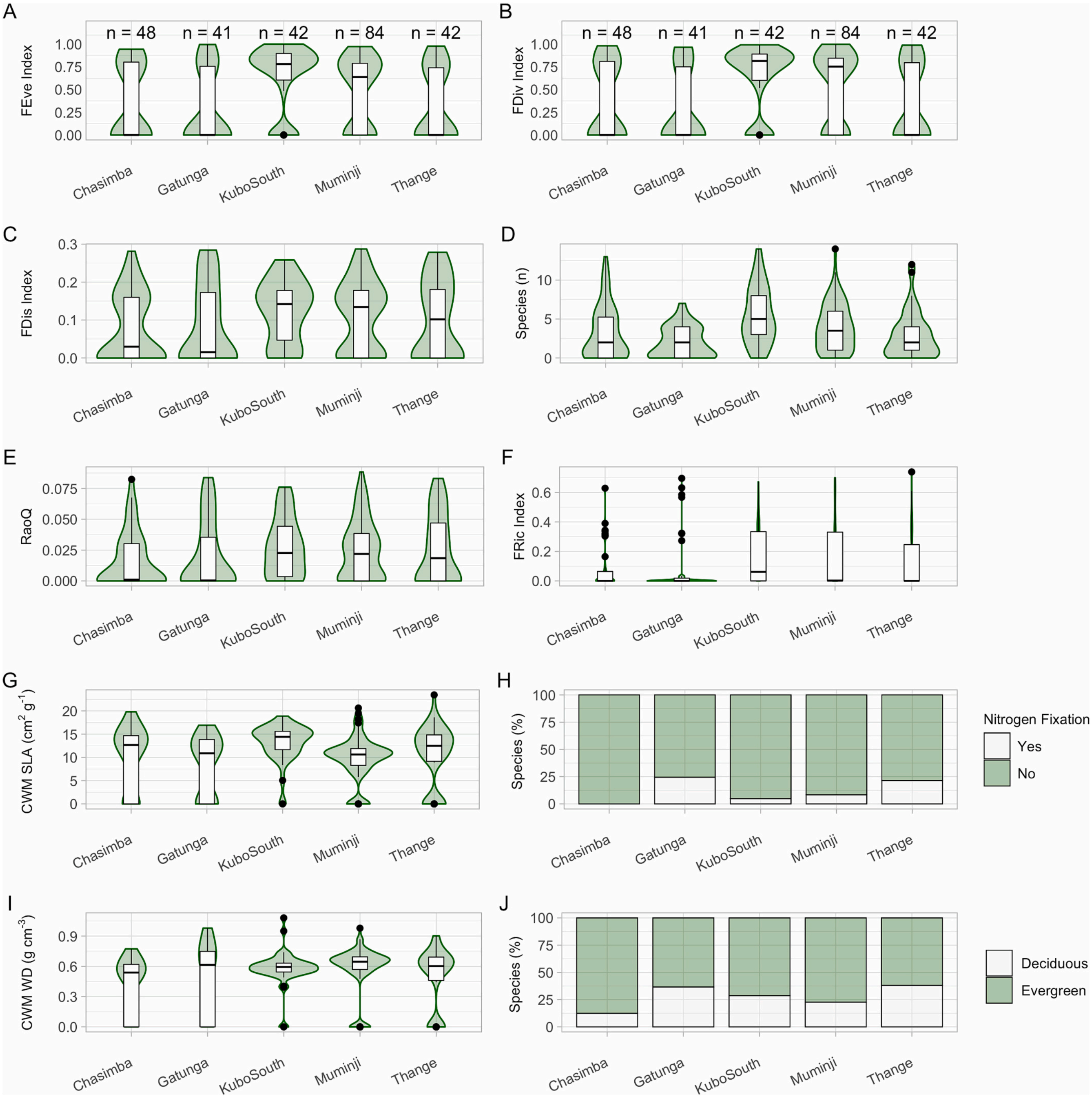

Fig. 5. Violin and boxplots (lower quartile, median, upper quartile) showing the variation in (A) functional evenness (FEve), (B) functional divergence (FDiv), (C) functional dispersion (FDis), (D) functional species richness (FSpRi), (E) Rao's quadratic entropy (RaoQ), (F) functional richness (FRic), (G) community-weighted mean of specific leaf area (CWM SLA), (H) community-weighted mean of nitrogen fixation (CWM NFix), (I) community-weighted mean of wood density (CWM WD), and (J) community-weighted mean of deciduousness (CWM Decid) across and within the five study sites in Kenya. The number of observations per site (n) is indicated above the top panels.

4.1. Soil properties

Sand content had a positive effect on K_{fs} across all five study sites (Fig. 7). This is in accordance with our initial hypothesis that coarser-grained soils have greater K_{fs} values than fine-textured ones, a relationship which is well established (Blackburn, 1975; Hillel, 1980; Mills et al., 2006; Medinski et al., 2009; García-Gutiérrez et al., 2018; Takoutsing et al., 2022). Sandy soils typically have high rates of infiltration and lower water retention capacity (Lozano-Baez et al., 2019). By contrast, fine-textured soils without aggregation have smaller pores which can, in cases such as vertisols, be further reduced during rainfall as a result of clay particles swelling, thereby inhibiting infiltration further (Medinski et al., 2009). We did not find a significant effect of soil pH on K_{fs} (Table 2), although high pH has been associated with low infiltrability (Mills et al., 2006; Medinski et al., 2010; Winowiecki et al., 2021), an effect which may be ascribed to an increase in clay dispersibility at higher pH values (Chorom et al., 1994). The range of pH in our study may have been too limited to find a relationship between K_{fs} and pH.

SOC also had a positive effect on K_{fs} (Fig. 7): this aligns with our

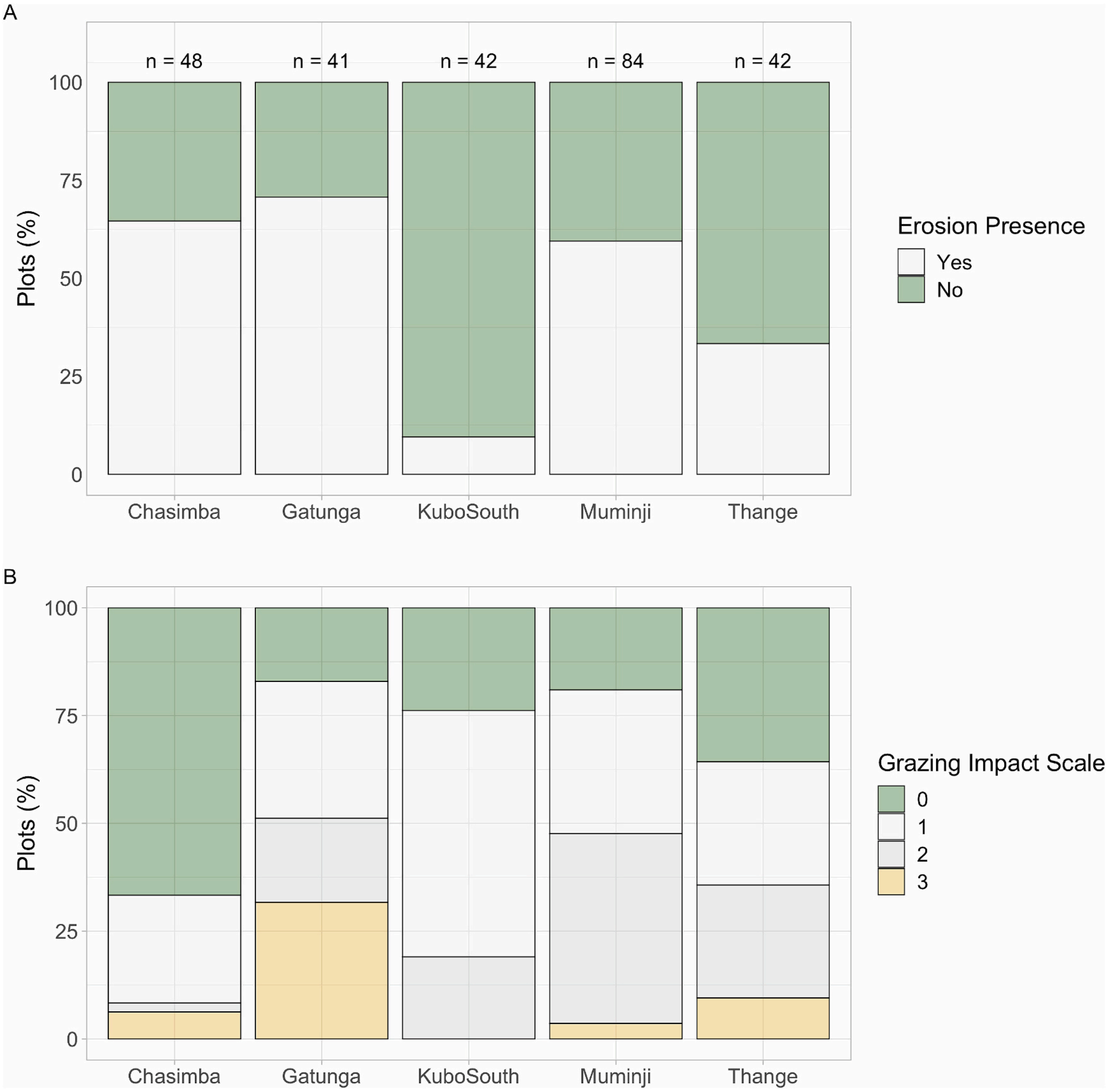

Fig. 6. Percentage bar charts showing the prevalence (% of plots) of (A) erosion presence and (B) impact of grazing across the five study sites in Kenya. The number of observations per site (n) is indicated above the top panel.

hypothesis and may be explained by the positive influence of SOC on soil aggregation and structure (Franzluebbers, 2002; Lado et al., 2004; Hao et al., 2020). This result broadly reinforces the findings of other studies which have shown a positive effect of SOC on K_{fs} and infiltration (Blackburn, 1975; Franzluebbers, 2002; Venter et al., 2021; Takoutsing et al., 2022), and expands this conclusion to tropical East Africa. SOC generally improves the physical structure of soils and increases soil aggregation, which involves both the formation and stabilization of soil structure (Faucon et al., 2017). Increasing the organic matter content in tropical soils may accelerate soil fauna activity which, in turn, results in more stable soil aggregates and greater macropore formation (Bargués Tobella et al., 2014). This further improves soil hydraulic properties and may contribute to explaining the positive effect of SOC on K_{fs}.

4.2. Land degradation

Our results indicate that erosion had a negative effect on K_{fs} (Fig. 7). This concurs with our hypothesis and with previous findings from landscapes in Rwanda (Winowiecki et al., 2021). Soil erosion often leads to reduced SOC and a decline in overall soil health (Dregne, 2002; Vågen and Winowiecki, 2013; Lohbeck et al., 2017). SOC and soil aggregation are strongly linked to infiltrability (Franzluebbers, 2002), which could explain why eroded soils have lower K_{fs}. Erosion also damages soil structure, reducing soil porosity and increasing surface crusting (Bossio et al., 2010), which may in turn negatively impact soil infiltration. Our model also contained a negative, although not statistically significant, interaction effect between sand content and erosion. This interaction effect on K_{fs} indicates that erosion also has a negative effect on K_{fs} in sandier soils, despite K_{fs} being inherently higher in plots with a higher sand content. Although our results indicate a strong negative impact of erosion on K_{fs} across our study sites, it is important to note that distinguishing the cause-effect relationship between erosion and K_{fs} is challenging. Where soil erosion caused by activities such as overgrazing or trampling by livestock (Marquart et al., 2020) leads to a loss in SOC this will further reduce K_{fs}, potentially resulting in a positive feedback loop and diminished resilience. In this scenario, land degradation is reinforced through decreased K_{fs} which results in more erosion and loss of SOC, in turn leading to further reductions in K_{fs}.

Grazing impact also had a negative effect on K_{fs} (Fig. 7). These results are in line with previous research which shows that high-intensity grazing decreases soil infiltrability (Gifford and Hawkins, 1978; Mwendera and Saleem, 1997; Basche and DeLonge, 2019; Marquart et al., 2020; Lulandala et al., 2021) and can be explained by the trampling action of livestock (primarily cows and goats) damaging soil

Table 2
Summary statistics for fixed effects and random effects of the optimal model explaining K_{fs} across all five study sites. The columns show estimates of the fixed effects (beta values), 95 % confidence intervals, and p-values (t-tests using Satterthwaite's method). The number of observations, sites and clusters within sites, the marginal and conditional R2, and the Interclass Correlation Coefficient (ICC) are indicated. The estimates are based on the standardized values of predictor variables. Sattertheewaite's method tests the null hypothesis, stating that $\beta\_n = 0$ (i.e. the effect of the fixed effect on Kfs = 0). The null hypothesis is rejected when $\beta\_n \neq 0$. The significant codes for p-values are: <0.1 = , <0.05 = *, <0.01 = ** and <0.001 = ***. The effect (and corresponding p-value) for the factor variable, erosion, is shown in comparison to the baseline reference level (i.e., 0, absence of visible signs of erosion).

Predictors	Estimates	Confidence interval	p-Value
(Intercept)	4.05	3.84 to 4.25	**<0.001*****
Sand Content (%)	0.39	0.22 to 0.56	**<0.001*****
Impact of Grazing (impact rating)	−0.09	−0.20 to 0.01	0.083
Presence of Erosion (binary)	−0.24	−0.44 to −0.04	**0.019***
Soil Organic Carbon (g C kg^{-1})	0.15	0.02 to 0.28	**0.022***
pH	0.02	−0.09 to 0.13	0.711
Woody Aboveground Biomass (Mg ha^{-2})	0.03	−0.06 to 0.12	0.512
Functional Evenness (index)	0.09	−0.01 to 0.19	0.068
Sand Content * Impact of Grazing	0.10	0.01 to 0.19	**0.022***
Sand Content * Presence of Erosion	−0.18	−0.38 to 0.01	0.057

Random effects	
ICC	0.07
$N_{Cluster}$	16
N_{Site}	5
Observations	257
Marginal R^2	0.19
Conditional R^2	0.25

structure, resulting in soil compaction and reduced soil porosity (Greenwood and Mckenzie, 2001; Martínez and Zinck, 2004; Savadogo et al., 2007). Moreover, the effect of grazing on soil compaction and health varies among different herbivore types, with cattle typically having a more negative effect than sheep or goats (Eldridge et al., 2017; Lai and Kumar, 2020). Soil compaction creates irregularities in the pore matrix, leading to lower infiltrability. Overgrazing by livestock can also lead to land degradation through reduced perennial grass cover (Castellano and Valone, 2007; Basche and DeLonge, 2019). Reduced vegetation cover can result in less SOC and increased bulk density, leading to decreased soil infiltration rates. Results from this study also show that the negative impact of grazing on K_{fs} was more pronounced in fine-textured soils than coarse-textured soils, which may relate to the presence of macropores that function as water conduits (Koorevaar et al., 1983). While sandier soils have high inherent macroporosity, the presence of macropores in fine-textured soils depends strongly on soil structure and aggregation. Hence the effects of soil compaction by livestock and SOC losses on infiltrability are greater in fine-textured soils. Although the negative effect of overgrazing on soil infiltrability has already been documented (Hiernaux et al., 1999; Savadogo et al., 2007; Lulandala et al., 2021), our findings support previous research on a larger spatial scale. These findings are particularly pertinent as animal husbandry and farming are key economic activities in sub-Saharan Africa.

4.3. *Vegetation quantity*

Surprisingly, the effect of vegetation quantity on K_{fs} was not significant (Table 2). Woody AGB exerted a slight positive effect on K_{fs} and improved the AIC score more than vegetation structure class (Table A.4). Although vegetation structure was not included in the final model, our characterization of sites by vegetation structure class did show that those containing more woody vegetation (bushland, wooded grassland) had a higher median K_{fs} than those with less (cropland, grassland). This suggests that vegetation quantity may indeed have a positive effect on K_{fs}, and merits further research into the topic. The lack of significance of woody AGB in the final model could be explained by limitations in the dataset. Specifically, the site with the highest median K_{fs} and the highest sand content, Kubo South, also had the highest woody AGB, and thus the positive effects of woody AGB on K_{fs} may have been masked by the stronger positive effect of sand content. The dataset would have benefitted from additional sites containing high woody AGB and low sand content. The lack of statistical significance between woody AGB and K_{fs} may also be accounted for by the effects of woody vegetation being captured by other covariates such as SOC or the functional diversity of woody vegetation.

Few studies have examined the effect of AGB on soil hydraulic properties. Mens et al. (2023) found a significant positive effect of woody AGB on K_{fs} in one of our study sites. Other studies demonstrated an effect of vegetation quantity on K_{fs}, but have been based on different proxies; woody plant density (Niemeyer et al., 2014), vegetation cover (Wilcox et al., 2008) and canopy cover (Bhark and Small, 2003; Magliano et al., 2015). These studies show that woody vegetation has a positive influence on soil hydraulic properties, possibly through enhanced litter inputs and root and soil faunal activity (Bargués Tobella et al., 2014). A large body of research relating to vegetation-soil hydrology interactions has examined the effects of land use conversion (Burch et al., 1987; Zimmermann et al., 2010; Leite et al., 2017; Sun et al., 2018) and forest restoration (Messing et al., 1997; Hassler et al., 2011; Mongil-Manso et al., 2021). These studies generally indicate that soil hydraulic conductivity is higher in forests (Chandler et al., 2018). One difference between this study and previous research is that our sites are in agriculture-dominated landscapes with a lower tree density than forests. In a meta-analysis about the impact of afforestation and agroforestry on soil infiltrability in the tropics, Ilstedt et al. (2007) found that afforestation had a greater positive effect on infiltrability in comparison to agroforestry. This suggests that potential outcomes of larger quantities of planted trees, such as increased leaf litter input, deep roots and shade, have a greater effect with increased tree cover (Ilstedt et al., 2007). In addition, our model did not capture other dynamics that have been previously observed between woody vegetation and soil texture. For example, Niemeyer et al. (2014) found that the influence of vegetational biomass on infiltrability was greater in fine-textured soils than coarse-textured soils, which is supported by previous research (Sobieraj et al., 2002; Hassler et al., 2011).

4.4. *Vegetation quality*

Our model showed that FEve of woody vegetation had a positive, although not statistically significant (Table 2) on K_{fs}, aligning with our hypothesis. Functional diversity in general, and FEve specifically, is an indicator of resource-use complementarity and niche differentiation. More belowground niches create more belowground microhabitats (Lamb et al., 2011) and an increase in the macropores created by roots and associated macrofauna (Bargués Tobella et al., 2014; Fischer et al., 2015). Niche differentiation is expected to enhance use of internal resources, increasing productivity by providing additional inputs and reducing losses (Cardinale et al., 2012). We suspect that reduced losses from erosion and increased inputs in the form of soil organic matter may underpin our findings. One of the main links between species diversity and soil infiltrability is SOC (Fischer et al., 2015; Liu et al., 2019; Kumar et al., 2021). Increased soil organic matter boosts soil porosity and aggregation and thereby increases K_{fs} (Mando et al., 1996; Ilstedt et al., 2007). Liu et al. (2019) found that plant species diversity had a positive impact on infiltration capacity, due to higher levels of organic matter input increasing aggregation and soil porosity. Higher ecosystem productivity through greater species diversity results in more SOC, leading

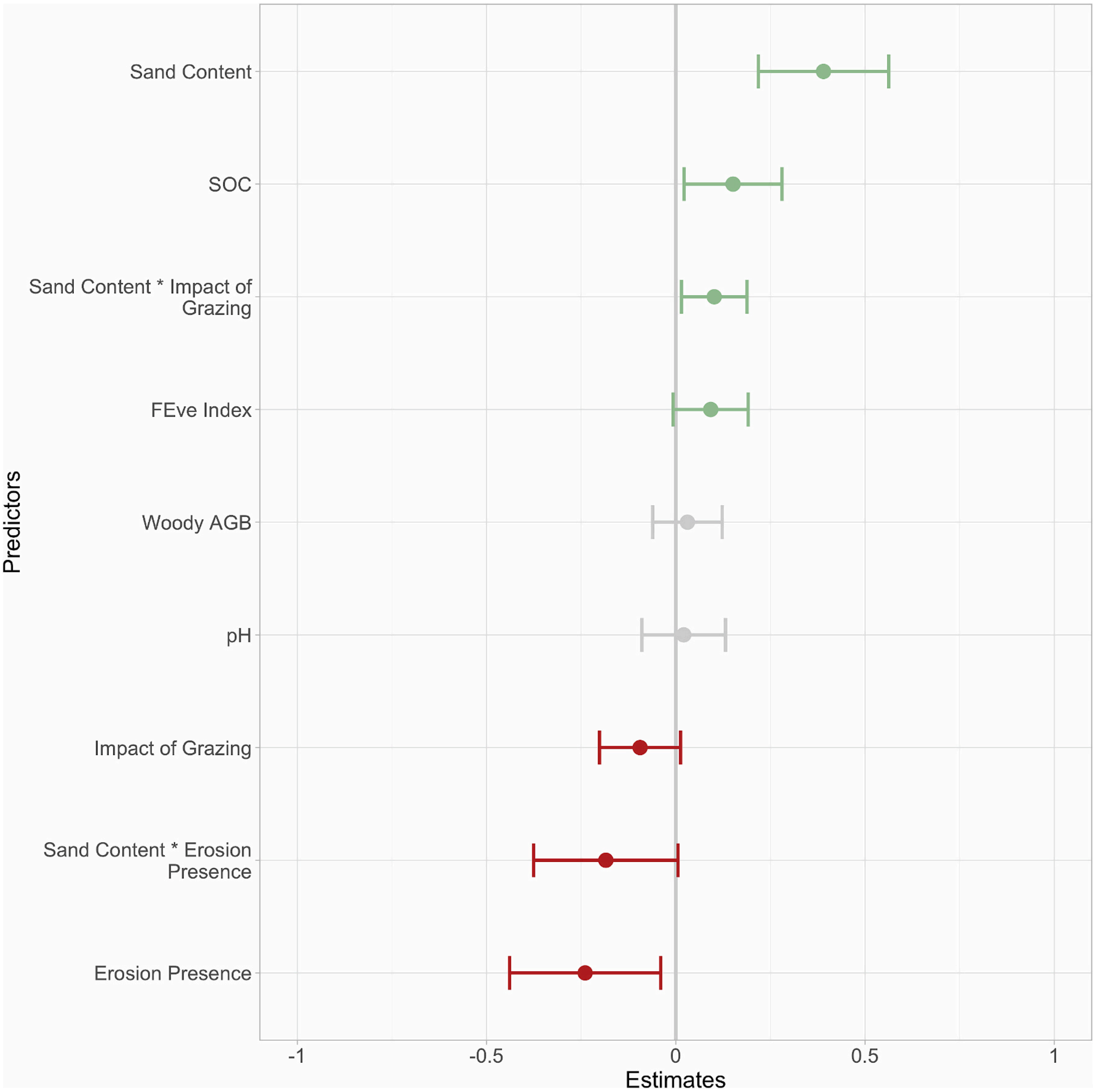

Fig. 7. Forest plot of fixed effects in the optimal model explaining topsoil field-saturated hydraulic conductivity (K_{fs}), graphed in descending order from highest positive impact on K_{fs} to highest negative effect. For each predictor, the standardized regression coefficients and their associated 95 % confidence intervals are shown. Green indicates a positive effect on K_{fs}, grey no effect, and red a negative effect.

to decreased bulk density, improved soil structure, greater porosity, and more soil aggregation (Liu et al., 2019; Kumar et al., 2021). While more research is needed into the interactions between aboveground functional traits and erosion (Faucon et al., 2017), Zhu et al. (2015) found a strong negative relationship between belowground FD and erosion. However, this relationship was not observed for FEve and was best explained by FDiv (Zhu et al., 2015).

The community weighted means (CWMs) of the four functional traits included in this study (deciduousness, nitrogen fixation, specific leaf area, and wood density) were not part of our final model (Table A.4). This contrasts with a study from a dry tropical watershed in Nicaragua, in which Niemeyer et al. (2014) found a significant positive correlation between specific leaf area (SLA) and saturated hydraulic conductivity. It also contradicts the results from Mens et al. (2023), in which CWMs of functional traits were more important in explaining variability in infiltrability than indices of FD in Muminji, Kenya. Mens et al. (2023) also found that species with an acquisitive functional strategy (e.g., high SLA and low leaf thickness) had a positive effect on K_{fs}, which was not observed in our results. Kumar et al. (2021) also identified several plant functional traits related to organic matter input that indirectly enhanced soil hydraulic properties by increasing soil porosity and organic carbon content. One explanation for exclusion of CWMs from our model could be that the SOC variable better encapsulated the effect of organic matter on K_{fs} than the indirect effect of SLA that previous research has described (Kumar et al., 2021; Niemeyer et al., 2014; Mens et al., 2023).

Although we used locally measured functional traits data whenever available, many of the species functional traits were derived from global databases. Locally measured trait data is more accurate given that trait values do not only depend on species identity but also on local conditions. This is particularly true for traits that are known to be more plastic, like specific leaf area (Cordlandwehr et al., 2013). In contrast, Mens et al. (2023) used local field-based data and found a positive relationship between K_{fs} and specific functional traits. This highlights the value of using site-specific data, and future research into ecosystem function and functional traits would benefit from field studies which measure such traits under local conditions. In addition, the global databases that we relied upon are limited in terms of the types of traits that are covered. Given our interest in effects on soil properties, it would have been relevant to study the effects of belowground functional traits, which are underrepresented in global databases (Bardgett et al., 2014).

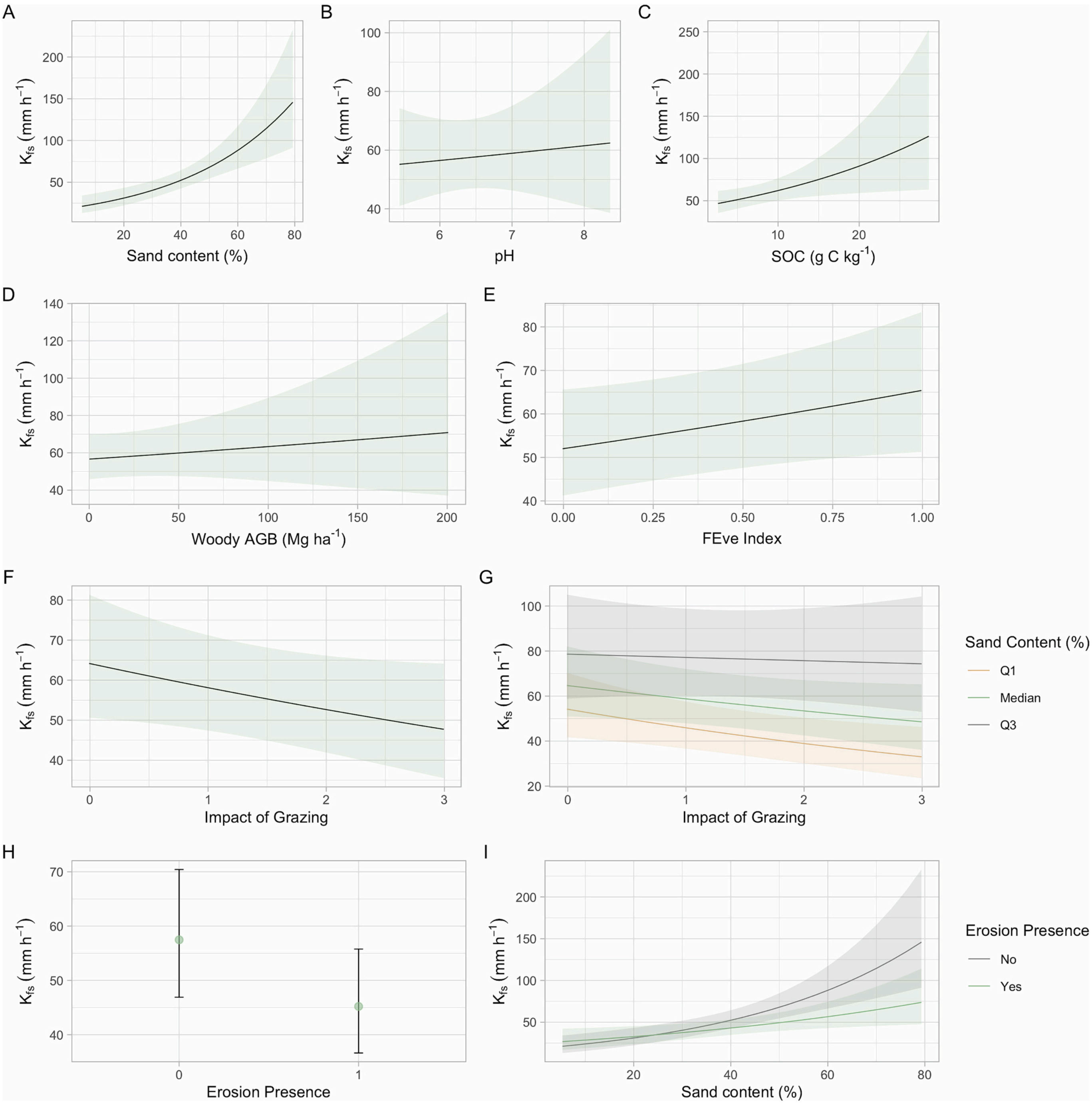

Fig. 8. Predicted topsoil field-saturated hydraulic conductivity (K_{fs}) as a function of predictor variables: (A) sand content, (B) pH, (C) soil organic carbon (SOC), (D) woody aboveground biomass (AGB), (E) functional evenness (FEve), (F) impact of grazing, (G) the interaction of grazing impact and sand content, (H) presence of erosion, (I) the interaction of erosion presence and sand content. The predicted K_{fs} in all graphs is a function of the predictor variables for mean values of all additional continuous predictor variables and the baseline level of the factor variable erosion (absence of erosion).

The capacity for roots to alter soil porosity (Bodner et al., 2014), and by extension K_{fs}, merits further investigation into the role of belowground functional traits on soil function (Freschet and Roumet, 2017; Gould et al., 2016; Hao et al., 2020), particularly soil hydrological function. Some studies have noted positive relationships between infiltrability and root dry weight density (Huang et al., 2019), fine roots and root length (Hao et al., 2020), and infiltration rates and root biomass as well as root length density (Leung et al., 2018). These results have been reinforced by more recent research. A European study comparing seven broadleaved tree species found that fine root density was the most important driver of changes in macroporosity, which in turn increased soil hydraulic conductivity (Webb et al., 2022). Fine roots can increase soil porosity through decreasing bulk density (Gyssels et al., 2005), while other factors such as root exudation and biotic root traits can positively affect soil structure and aggregate stability (Bardgett et al., 2014). Specific functional traits related to roots may indirectly affect soil hydraulic properties by reducing erosion rates.

4.5. *Implications for management*

Our results suggest that soil hydrological function could be increased by implementing management practices that positively affect infiltrability. As our findings confirmed the positive effect of SOC on K_{fs}, they highlight the potential to increase water security by adopting land management practices that enhance SOC (Vågen et al., 2005; Minasny et al., 2017), which include the addition of manure, reduced tillage, agroforestry, or improved grazing management (Chen et al., 2015; Conant et al., 2017). Collectively, the effects of implementing these practices would extend beyond addressing water security to benefit climate change mitigation, soil health and food security as well (Lal, 1987; Lal, 2010; Lal, 2016; Minasny et al., 2017). Furthermore, preventing soil erosion is an important strategy to reduce the loss of SOC and to enhance soil health, soil porosity, and soil structure – all factors which are strongly linked to K_{fs}. To prevent escalating land degradation, further reducing K_{fs} and undermining water security, restoration measures must be adapted to local conditions. Implementing livestock grazing management practices that prioritize soil health through less intensive grazing (Chen et al., 2015; Eze et al., 2018), silvopastoralism (Jose and Dollinger, 2019), or through grazing exclusion to allow for vegetation regeneration (Descheemaeker et al., 2006; Mekuria et al., 2007; Qasim et al., 2017; Lulandala et al., 2021) may be effective strategies for enhancing water security and improving overall soil health.

5. Conclusion

This study aimed to determine the key variables that influence infiltrability at the landscape scale, a focus that is lacking in contemporary research. Through considering larger spatial scales and more diverse landscapes than previous research on the topic this work adds to existing knowledge concerning soil hydraulic properties in the tropics. Our results show that K_{fs} can be enhanced by adopting management practices that build soil health through increasing SOC content, reducing erosion, and limiting livestock grazing pressure. In addition, our findings suggest that increasing the functional diversity of woody vegetation can improve K_{fs}. These findings may assist implementation of restoration strategies in ecosystems where management will be consequential. By adopting management practices that positively affect K_{fs}, freshwater scarcity in the tropics can be addressed and minimized, safeguarding human livelihoods and sustainable futures.

CRediT authorship contribution statement

David Falk: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Leigh A. Winowiecki:** Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – review & editing, Project administration, Funding acquisition. **Tor-Gunnar Vågen:** Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – review & editing, Funding acquisition. **Madelon Lohbeck:** Conceptualization, Methodology, Formal analysis, Writing – review & editing. **Ulrik Ilstedt:** Conceptualization, Methodology, Writing – review & editing, Funding acquisition. **Justin Muriuki:** Writing – review & editing. **Alex Mwaniki:** Writing – review & editing. **Aida Bargués Tobella:** Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – review & editing, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Ulrik Ilstedt reports financial support was provided by Swedish Research Council. Aida Bargues Tobella reports financial support was provided by Swedish Research Council Formas.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2023.168038.

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