Comparing fine-scale structural and hydrologic connectivity within unimproved and improved grassland

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Funding information
University of Exeter; INTERREG project (Climate resilient community-based catchment planning and management); Devon Wildlife Trust; Environment Agency

Abstract
Grasslands vary with diverse forms and functions ranging from monocultures of perennial rye grass to more biodiverse unimproved grasslands which cover around 5% of Europe. Despite the broad diversity of grassland types, within environmental and flood risk models grasslands are frequently represented by a singular set of hydrological and structural parameters which belies their diversity and complexity. This study aimed to determine empirically the extent to which improved versus unimproved grasslands exhibit different hydrological connectivity. Working in SW England at neighbouring field sites with comparable slopes and rainfall regimes, we used unpiloted aerial vehicles to survey a tussocky Molinia caerulea dominated unimproved grassland field (MCUG) field and a Lolium perenne dominated improved grassland (LPIG) field. Using digital photogrammetry workflows applied to the overlapping aerial images, we produced a digital surface model (DSM) at 0.03-m resolution from which flow pathways were modelled using GIS and compared with 1-m LiDAR and DSM produced by a global navigation satellite system (GNSS). MCUG had longer, tortuous pathways through the dense tussock network with a drainage density of 2.54 m m\(^{-2}\). This was significantly greater than drainage density in the LPIG (1.82 m m\(^{-2}\)). As a result of this study, we rescaled the Manning’s n value for MCUG according to photogrammetrically-derived roughness values. We suggest it should lie between 0.075 and 0.09. Our data shows that MCUG can play an important role in reducing overland flow impacts when compared to LPIG through lower connectivity which can delay run-off to rivers.

KEYWORDS
connectivity, flood management, grasslands, microtopography, UAV, unimproved grassland

1 INTRODUCTION

Grasslands are an important component of landscapes. For example, they comprise 37% of the UK’s land area (DEFRA, 2012) and just over a fifth of land area across the European Union (Eurostat, 2020). Grasslands are usually broadly described as ‘improved’, ‘semi-improved’ or ‘unimproved’ with the former dominated by intensively managed single species Lolium perenne perennial ryegrass (Laidlaw & Frame, 2013), while the latter are characterised by more diverse swards with much more variable structural complexity (Bullock et al., 2011). ‘Semi-improved’ is a transitional category but largely less diverse than unimproved grasslands. Within eco-hydrological studies and environmental models, particularly rainfall/run-off and flood risk models, grassland diversity is poorly represented, with usually a single
hydrological parameter set describing grassland function. Such a simplification is problematic because there is evidence that unimproved and improved grassland exhibit significantly different eco-hydrological behaviour from each other, particularly in terms of their potential connectivity and also in terms of their run-off generation and contribution to flooding downstream (Bilotta et al., 2008). This paper will refer to ‘connectivity’ meaning structural connectivity, and ‘disconnectivity’ meaning the disruption of such connectivity in space. Connectivity herein refers to static spatial patterns in the landscape which influence water transfer and flow pathways (Bracken et al., 2013).

Improved grassland is known to be a source of substantial surface run-off due to the high levels of soil compaction, high surface and subsurface drainage connectivity and low surface roughness (Bilotta et al., 2008; McIntyre & Marshall, 2010), the latter being exemplified by Manning’s ‘n’ value for grasslands being five times lower than woodlands (Chow, 1959). Improved grasslands contribute 60% of the nitrate, 25% of the phosphorus and 75% of the suspended sediment pollution in UK rivers, costing the water industry approximately £120 million per year from the contamination of drinking water via diffuse pollution (Holden et al., 2014; Pretty et al., 2000). Conversely, some work has found that hydrological flows and connectivity can be quite different in unimproved grassland compared to improved grassland. For example, Puttock and Brazier (2014) discovered low connectivity within mature Rhôs pasture/Culm grassland (Molinia caerulea pastures), due to the lack of field run-off synchronicity with nearby river peaks. Corroborating this, Bond et al. (2020) found lower flow velocity in rush dominated-pastures compared to improved grassland due to denser vegetation and higher surface roughness. Despite these differences, grassland heterogeneity is rarely acknowledged in hydrological models. For example, in those which use roughness coefficients (e.g. Manning’s n) to simulate surface run-off velocity and volume, areas with ‘grass’ land cover are distinguished only as having ‘short’ or ‘tall’ grass—which fails to acknowledge the variable hydrological processes linked to spatial changes in structure (Chow, 1959). For example Collins et al. (2012), Hansen et al. (2007) and López-Vicente and Álvarez (2018) all grouped grassland as a single hydrological response unit when modelling agricultural systems. There is not currently an evidence basis underpinning a more nuanced classification of ‘grasslands’ in such models.

As awareness of flood risk under climate change grows, different approaches to flood management are being explored at national and international levels. There is growing interest in natural flood management (NFM)—which works with natural processes to reduce flood risk by using environmentally sensitive techniques to manage sources and flow pathways of flood waters (Dixon et al., 2015). NFM also favours methods that store water in landscapes and increase hydrological residence time by reducing connectivity. However, unlike the current dominant engineering approach to flood management, NFM lacks an established evidence base describing how different techniques reduce flood risk which is needed to support future flood management decisions (Burgess-Gamble et al., 2017; Dadson et al., 2017; Ellis et al., 2021). While knowledge of the hydrological processes that reduce flood risk are well established for woodland (e.g. increased evapotranspiration) (Odoni et al., 2010; Quinn & Wilkinson, 2019; Thomas & Nisbet, 2007), grasslands have been comparatively overlooked, despite their large spatial extent. Therefore, more research into grassland eco-hydrology, spatial heterogeneity and connectivity is vital if their role in NFM is to be understood.

In Europe improved grassland is associated with intensive management including, subsurface drainage, regular fertiliser applications and high density animal grazing (Bilotta et al., 2008; Laidlaw & Frame, 2013; Pilgrim et al., 2010). Unimproved grassland conversely now forms a small component of grassland coverage; covering an estimated 5% of European grassland having decreased with agricultural expansion and the need for permanent grazing pasture (Peyraud et al., 2014). Unimproved systems are highly biodiverse, owing to the lack of treatment with fertiliser and with low intensity agriculture (Blakesley & Buckley, 2016). There is a need to understand unimproved grassland hydrological structure, function and particularly structural connectivity.

M. caerulea dominated unimproved grassland (MCUG) is an example of an unimproved grassland with very little understanding of the hydrological processes within the grassland, such as surface water storage. M. caerulea is a type of wet, unimproved grassland which is relatively common across South-West England and NW Europe, and dominated by tussock structures approximately <0.5-m diameter and <0.5-m in height (Pilgrim et al., 2010; Taylor et al., 2001). In South-West England MCUG and rush pasture fields are known as Culm grassland as these overlie the Culm measures, an area of upper Carboniferous shale geology with seasonally saturated clay soils. Culm grassland was once extensive in North Devon and Cornwall, but due to drainage for agricultural expansion only 5% of MCUG remains compared to 1950 extents (Devon Wildlife Trust, 2014). These environments are known to store water above and below the surface, but very little is known of the surface hydrological processes and connectivity of these grasslands which may provide NFM benefits (Puttock & Brazier, 2014), despite a widespread goal to reinstate areas of Culm grassland for flood risk management across Devon.

Research has shown that improved grassland exhibits enhanced hydrological connectivity compared to unimproved grassland (Bilotta & Brazier, 2008). This research aims to develop a deeper ecohydrological understanding of structure and function within both improved and unimproved grasslands, focussing upon LPIG and MCUG, at high spatial resolutions and at the field scale to deliver evidence for NFM. The overall aim is as follows:

To improve understanding of structural connectivity within MCUG in comparison to LPIG ecosystems.

This was achieved by testing the following hypotheses:

**Hypothesis 1.** $H_0$: There is no significant impact of tussocks upon surface flow pathways and structural connectivity.

**Hypothesis 2.** $H_0$: There is no significant difference between unimproved and improved grassland drainage density.
Hypothesis 3. $H_0$: Different survey methods deliver quantitatively different descriptions of vegetation and topography structures (in terms of accuracy and precision).

2 | METHOD

2.1 | Study site

Two field sites, typical of LPIG and MCUG of NW Europe were located in Meeth, central Devon (UK) (Figure 1). A $\sim$1.3-ha field on MCUG at Ash Moor Nature Reserve was used as the study site (lat 50.859090, long $-$4.090009). This is an established field of species rich MCUG with other species including Succisa pratensis, Holcus lanatus and Potentilla erecta. It has been in this ecological state for at least two decades, has never been tilled and thus represents the typical vegetation assemblages that have prevailed in unimproved grasslands since woodland clearance with limited management. The field is used for low intensity cattle grazing between May and October and included recreational footpaths cross-cutting the site. The MCUG field was burned (a local practice known as 'swaling') as part of a 3- to 4-year management cycle, which afforded the opportunity to survey the tussocky structure of the vegetation at high resolution without interference by the overlying deciduous leaves of the grassland. A nearby $\sim$2.7-ha field of LCIG was used as a comparison site (50.855980, $-$4.077108), with a history of high stock density grazing ($\sim$6 livestock unit/ha). Despite an area of soft rush (Juncus effusus) being present towards the base of the field, the field is still classified according to the National Vegetation Classification as improved grassland by a botanical survey undertaken as part of the project. Given the nature of the hypotheses, field sites used needed to be consistent. The MCUG and LPIG fields were chosen for their close proximity with the same underlying soil type (Wickham 2) and climatic regime. A 1-m resolution DTM derived from LiDAR was used to measure the field slopes which averaged 2$^-3^\circ$ on both. This meant no marked differences in hydrological processes caused by slope, soil type or other climatic changes.

2.2 | Data collection

In order to collect high spatial-resolution digital surface models of the paired grasslands, an Unpiloted Aerial Vehicle (UAV) was deployed. The DJI Mavic Air is a portable, lightweight UAV (430 g) with a high quality camera (2.3" CMOS, 12 mega pixels) which was easy to transport in the tussocky field. Three UAV flights were undertaken March, April and May 2019 following the same flight plan after the burning of the MCUG field (this burning took place in March 2019), as conditions such as water content and vegetation regrowth changed during this period. A challenge faced by this research is that vegetation can obscure M. caerulea tussock structures, meaning the final UAV product may not be an accurate representation of tussock connectivity, particularly in peak greeness. Vegetation obscuring fundamental aspects of a UAV survey has been identified by Dandois et al. (2017), Fraser et al. (2016) and Javernick et al. (2014). The controlled burning of the site meant an opportunity to survey just the soil-forming tussock structure without vegetation obscuring the microtopography.

FIGURE 1 (left) the two fields used for this study (source: Esri). (a) M. caerulea tussocks. (b) Swaling of a M. caerulea site. (C) LPIG field (source: author’s own)
Pre-programmed flight plans were made using Pix4D (4.9.0), flying at an altitude of 40 m at a speed of 8 m s⁻¹ with ground pixel resolution average of 1.6 cm/pixel. Overlap was set to 85% for both frontal and side overlap following the recommendations of Dandois et al. (2015), Fawcett et al. (2019) and Torres-Sánchez et al. (2018). The UAV flew linear flight lines across the across each field, first parallel to the NE edge of the field, then perpendicular to form a grid. On each grid intersect an image was automatically captured. Optimal conditions were present in May 2019 (including lighting, wind, no surface water and removal of burned material) and this was selected as the best quality flight. Fifteen ground control points (GCPs) were spread evenly across the field and left secured over the three survey periods to minimise effects such as doming (Fawcett et al., 2019; James et al., 2017; Tonkin & Midgley, 2016). GCPs were then surveyed using a global navigation satellite system (GNSS), which provided sub-centimetre accuracy of GCP positions from which to process UAV imagery. GNSS data were processed using a receiver independent exchange format (RINEX) system to provide accurate GCP positioning to British National Grid co-ordinate systems (~0.005 m) which can later constrain elevation models produced from the data (Tonkin & Midgley, 2016).

2.3 Data processing

The images obtained from the UAV flights over MCUG and LPIG fields were imported into Agisoft Metashape (1.5.3) to make the digital surface model (DSM) by structure from motion (SfM) photogrammetry. This software has been a successful choice for projects, producing DSMs of vegetation structures such as trees and river channels (Jaud et al., 2016; Javernick et al., 2014). Firstly, images are aligned to produce tie points whereby images overlap. This produces a sparse point cloud that approximately shows the topography of the grasslands (tie point density 7.71 points per m²). The 342 photos were used for DSM construction in the LPIG field, 126 in the MCUG field. The GCP coordinates were imported and manually identified from images. Five GCPs were used as check points in the build as independent measures of model accuracy and 10 GCPs were used as control points to reduce systematic error in photogrammetric processing following James and Robson (2014). A dense point cloud (DPC) was then generated on the highest accuracy setting (key point limit set at 80,000 and tie point limit at 8000, no depth filtering) with camera optimisation parameters following the recommendations of James et al. (2017). Pixel density for the DPC was 1492 pix/m.

Minimising and quantifying error of the DPC was vital to assure that grassland connectivity conclusions were valid. The first step was reducing the difference in error between control and check points through optimisation of the bundle adjustment process (James et al., 2017). The root-mean-square error (RMSE) is a common measure for DPC difference between points (Sanz-Abblanedo et al., 2018). The relative precision ratio was calculated for both field sites by dividing the UAV survey height by the RMSE (Smith et al., 2016). This measure gives a good indication of average model performance but does not identify where spatial variability is greatest or least which can be identified with precision analysis but was deemed not appropriate for this application (James et al., 2017; Milan et al., 2007). Surfer (version 13.5.583) was used for DSM generation as Agisoft Metashape does not permit the same end-user control over DSM generation compared to Surfer (Bakker & Lane, 2017; Glendell et al., 2017). Surfer allows the method of DSM generation to be chosen, and allows the user designation of the DSM pixel size. The DSM for both fields was modelled using ordinary spherical kriging (Luscombe et al., 2015).

The measurement of tussock grassland structures with remote sensing approaches has had limited exploration (Fahey et al., 1998). Consequently, it was necessary to validate the DSM against independent measurements in order to address the proposed hypotheses. This validation also allowed for comparison of survey techniques as per hypothesis 3. To create the validation DSM, GNSS with a spatial x, y and z accuracy of 0.02 m was used to thoroughly survey all ground and tussock points within a 3 × 3 m area delivering 317 points in total. At every change in elevation a point was recorded on the DPGS, including multiple points across tussock tops. After post-processing using a RINEX system, these points were interpolated using ordinary spherical kriging within ESRI ArcGIS Pro (version 2.4.0). The same process of kriging was then used upon the same area of DPC generated by the UAV for comparison. Semivariogram analysis (ordinal spherical kriging) was used to characterise the spatial structure of each dataset and the semivariogram parameters compared to assess similarities between the kriged products derived from the DPC and GNSS.

2.4 Hydrological processing

Once DSMs of each field were produced surface flow pathways could be modelled to infer function from structure. Firstly, the location and size of tussock tops were identified using a modified script from the R lidR package (version 3.0.3), a package developed for identifying tree properties within canopies from a DPC (Roussel et al., 2019) although not so far used in tussock grassland systems. The use of a DPC for tussock identification was preferable to DSM analysis as there can be error introduced around tussocks structure during the production of a DSM from the DPC (Bater & Coops, 2009). Ground points were identified and tussocks classified using a set height threshold (0.1 m above normalised ground) to identify tussocks of 0.1–0.5 m in height. From this, a raster layer describing tussock area was extracted. Trees in the LPIG and MCUG field were also segmented using the same method.

The subsequent raster layer meant that trees could be excluded from hydrological analysis. This avoided trees biasing the hydrological analysis as the software would otherwise have allowed these to impact flow pathways. Of note is the fact that trees can be chosen to be included or excluded from this workflow depending on whether they are deemed to exert important controls on flow paths. The standard deviation (σ) of z points of the DPC was plotted in Surfer (version 13.5.583) across the whole of each field as a proxy for surface...
roughness as curved and rougher surfaces will have greater $\sigma$ in the $z$ coordinate (James et al., 2017).

To perform surface water hydrological analysis, the DSM needed to be filled for sinks or data gaps to predict potential flow pathways through the specified area. ArcGIS fill function has been shown by Venticinque et al. (2016) and Pareta and Pareta (2012) to be suitable for filling DSM gaps in large river basins. However, in a landscape such as a tussock field we felt that adopting this method could have resulted in loss of valuable depressions which we hypothesised were essential structural attributes that impact surface water storage in MCUG (Jenkins & McCauley, 2006). Instead, the optimised pit removal function uses a combination of cut and fill to minimise loss of fine topographic features within this landscape (Soille, 2004). This function was applied to both the experimental field and the control field.

The hydrological toolset within ESRI ArcGIS Pro (version 2.4.0) was used for flow pathway replication. Firstly, flow direction of every cell within the raster was computed from the DSM in D8 directions. Flow accumulation then identified areas of accumulation into each downslope raster cell, which was then reclassified to reflect accumulation of different drainage areas (10, 20, 50, 100, 200, 500 and 1000 m$^2$). The stream order function produced a raster of flow pathways based on drainage areas, and the same process was applied to a 1-m LiDAR DSM for comparison with commonly used data in hydrology (Barber & Shortridge, 2013). Drainage density (Dd) was calculated using the line statistics function and was calculated as the total length of flow pathway per unit area. This parameter can be used as a proxy for connectivity within a field (Godsey & Kirchner, 2014). Each field was divided into a grid (1, 4, 25, 100, 400, 1225 and 2500 m$^2$) within which flow pathway length was calculated. This meant that fields of different sizes could be compared for connectivity parameters; higher Dd values indicated lower connectivity as more pathways were present. Each grid was then compared using a Welch two-sample T-Test to test for significant difference in flow pathway length and therefore connectivity. A Welch two-sample $T$ test was used as the data were normally distributed with independent samples. Flow pathway values were then extrapolated using flow pathway averages ($\pm$1 standard deviation) to provide a rough prediction of the flow pathway length in a larger $M$. caerulea and LPIG field up to 50,000 m$^2$. A summary of the entire data processing workflow is summarised in Figure 2.

3 | RESULTS

3.1 | DSM

The DSM of the MCUG field and LPIG field are shown in Figure 3. Both DSMS were produced at a fine spatial resolution of 0.03 m from an average point density of 1492 pix/m. The averaged error within the DPC for each field is shown in Table 1. Both models had a relative precision ratio of 1:200. Tussocks were dense in the MCUG field covering 43% of the field surface area (2.3 tussocks per m$^2$). The use of a Welch two sample T-test showed the LPIG field was significantly different in surface roughness to the $M$. caerulea field (MCUG $n = 3$ million, LPIG $N = 5.2$ million, $p = 0.02$, ≥0.095).
3.2 Validation

The results of the GNSS and SfM photogrammetry comparative 3 m x 3 m plots are shown in Figure 5. Both show the basic tussock structure of the landscape. The points were interpolated using ordinary spherical kriging, the semivariogram generated for the kriged points are shown in Figure 6 and Table 2, which provides details of the two datasets. The range is the point at which no further increase in distance results in increased dissimilarity in semivariance. The range of the SfM photogrammetry DSM was 57% greater than the GNSS DSM (0.47 and 0.30). These values are similar to the size of a tussock and the semivariogram parameter confirms the system structure. The greater UAV value is likely linked to the greater density of points per m² (Table 2). The GNSS DSM was subtracted from the SfM photogrammetry DSM to understand differences in the two methods. The two DSMs show that tussocks are still fundamentally located at the same locations, though some variation in height and location exist and contributes to differences in semivariance parameters (Table 2). There is an average x/y/z error of 0.10 m between the GNSS and DPC. This may reflect small x/y error within the UAV DSM, suggesting
FIGURE 4  Roughness derived from standard deviation of Z points of MCUG (a) and LPIG (b)

FIGURE 5  Structure from motion (SfM) photogrammetry (a) and global navigation satellite system (GNSS) (b) comparative 3-m × 3-m plots

FIGURE 6  Semivariogram of global navigation satellite system (GNSS) and structure from motion (SfM) photogrammetry plots
Tussocks are in slightly different location to reality. The similarity in values in Table 2 shows that the UAV is a validated close representation of tussock reality and therefore valid conclusions of flow pathways can be made from the SfM product.

### 3.3 Flow pathways

Segments of overland flow pathways are shown in Figure 7a–c, with colours corresponding to m² of drainage (e.g., 50 m²). MCUG has long, sinuous surface flow pathways through the dense tussock network (Figure 7a). Flow pathways in the LPIG were straight and more in-line with the more planar slope in comparison (Figure 7b). Flow pathways in the soft rush area of the improved field show some non-linearity from the increase in surface roughness, but overall the flow pathways align downslope in a linear manner. In both fields, where footpaths or wheel tracks are present these form major flow pathways through the field (>100-m² drainage). The LiDAR DSM derived flow pathways lack the level of detail observed in the SfM photogrammetry derived products (Figure 7c).

|                      | Point density (per m²) | Nugget | Partial sill | Range | Lag |
|----------------------|------------------------|--------|--------------|-------|-----|
| GNSS                 | 38.44                  | 0.002  | 1.313        | 0.30  | 0.26|
| UAV DPC              | 14892.89               | 0.002  | 0.990        | 0.47  | 0.45|

**Figure 7** (top to bottom) flow pathways through MCUG and LPIG. (bottom) flow pathways produced by the same analysis using 1-m LiDAR in the MCUG field.
3.4 | Drainage density

MCUG had on average 2.54 m m$^{-2}$ of flow pathway, which was 1.4 times greater than that of LPIG at 1.82 m m$^{-2}$. Flow pathway length increased with area in MCUG as shown in Figure 8. The use of a Welch two sample T-test showed there was no difference in mean flow path length between the two fields below 1225 m$^2$ ($p = 0.041$, ≥0.95) (Table S1). There was also a significant difference at 2500 m$^2$ ($p = 0.004$, ≥0.95). When extrapolated using flow pathway averages up to 50,000 m$^2$ (5 ha), the difference in flow pathway length continues to increase, as shown in Figure 8. Upper and lower limits of Dd were produced by calculating minimum and maximum flow pathways per unit area from observed flow pathway data. The contrast in Dd between unimproved and improved grassland cover increases with area, and the gap between the two vegetation types continues to increase. Figure 9 shows the SfM derived drainage density plotted against drainage density of the LiDAR DSM flow pathways, from which a notable difference between the two methods can be seen.


4 | DISCUSSION

In this observational study, we demonstrated that SFM photogrammetry-derived surface models can deliver fine-grained new insights into the ecological structure and hydrological function of unimproved and improved grassland fields. Characterisation of these structures at 0.03-m spatial resolution has allowed us to show that the tussock structures within unimproved grasslands cause significant reductions in hydrological connectivity over areas greater than 1225 m². The calculation of z value $\sigma$ from SFM-derived DSM showed unimproved grassland structures were significantly rougher than those in improved grassland, which highlights that the *M. caerulea* tussocks reduce surface flow pathway hydrological connectivity. The assumption that MCUG fields had reduced connectivity in comparison to an LPIG was tested using flow pathway models. Results showed UAV derived SFM DSM had 33 times greater spatial resolution compared to what could be delivered from airborne LiDAR products. The resulting flow pathway models showed the dense tussock structure of *M. caerulea* grasses resulted in more tortuous flow pathways, on average 1.4 times longer those found in the LPIG system. This finding agrees with conclusions that tussocks in grasslands intercept flow pathways, such as Cammeraat and Imeson (1999) and Quinton and Carey (2008). The study advances understanding of surface processes beyond the plot-scale soil moisture plots of unimproved grassland work by Ludwig et al. (2005) and Wallace and Chappell (2020) by including surface flow pathways over a field extent. We also demonstrated that the significant difference in flow pathway length between unimproved and improved grassland increased with area (Figure 8), which we tested to a maximum extent of 5 ha. This difference suggests that over larger areas of unimproved grassland, potential flow attenuation due to flow pathway length increasing will grow.

How do tussocks impact surface flow pathways?

Our work has proven that SFM photogrammetry offers a capable and scale-appropriate method for describing surface structures that impact hydrological surface flow pathways. Z point error indicated that MCUG had a significantly rougher surface than LPIG (0.03 m versus 0.01 m) (Figure 4). Surface roughness influences connectivity in fields by increasing flow pathway length and creating surface depressions for water storage (Bracken & Croke, 2007). In response to hypothesis 1, we showed that the MCUG field was significantly rougher than the LPIG field through z point error ($\sigma$), as rougher surfaces produce more z error on nadir UAV flights than planar surfaces (James et al., 2017; Shepard et al., 2001). Point error was on average 200% greater in MCUG fields than LPIG fields. As a result of this finding, we recommend the Manning's n for rough, tussock structure grasslands be set to reflect this 200% roughness increase to a value range of between 0.075 and 0.09. This would be suitable in comparison to the less rough improved grassland currently classified at 0.025 to 0.03.

As suggested by Dadson et al. (2017), the lower connectivity in complex environments has potential NFM benefits when soils become saturated by prolonged rainfall or during high intensity events with infiltration excess overland flow. When overland flow is generated, the same volume of water has further to travel through the tussock network in the unimproved grassland, than in the better-connected improved grassland. Although hydrographs were not measured here, other work from woodland ecosystems shows that where flow pathways through landscapes become more disconnected and friction due to surface roughness increases, the peak of the hydrograph is delayed (Papanicolaou et al., 2018; Thomas & Nisbet, 2007). The lengthier flow paths within the *M. caerulea* tussocks may thus result in greater residence time of water within fields enhancing processes of soil infiltration, root uptake and evapotranspiration (Wallace & Chappell, 2020). This residence time and uptake of surface water will likely be dependent on the time of year which would need further exploration. Results of flow pathway mapping from this work indicated that unimproved grasslands with tussock structures could deliver a slower overland flow through such landscapes. This has also been found in other vegetation structures. For example, Thomas and Nisbet (2007) modelled the changing of surface roughness by woody debris increased flood storage up to 71% and delayed flood peaks up to 140 min in a 1690 km² catchment by increasing residence times of water within woodland and slowing surface flow through biomass. Upland systems have previously been studied to establish the extent to which surface roughness changes and influences hydrological processes following restoration. For example, Bond et al. (2020) and Holden et al. (2008) reported that increased *Sphagnum* and *Juncus* cover influenced overland flow velocity and surface water uptake by vegetation. Such environments are similar to the MCUG complex microtopography and roughness implying it too can reduce flood-risk reduction benefits.

There are also further benefits—for example, MCUG fields will have less soil erosion due to the more sinuous pathways which is otherwise a common problem and cause of land degradation in poorly managed improved grassland fields (Brazier et al., 2007). These pathways have been observed in other tussock grassland; in one study of wetland sedges and *Carex stricta* tussocks, tussock structure microtopography made an ideal habitat for a variety of other plant species to colonise which increased surface roughness and sediment trapping (Werner & Zedler, 2002). We argue with the evidence gathered in this work, that *M. caerulea*-dominated unimproved grassland has great potential as a form of NFM through delivering increased surface roughness and more sinuous flow pathways compared to improved grassland. There are also multiple further environmental benefits from unimproved grassland restoration such as increased flora and fauna biodiversity and carbon sequestration (Puttock & Brazier, 2014).

Do unimproved and improved grasslands have significantly different drainage density?

We found a significant difference in drainage density at 1225 m² between MCUG and LPIG, the difference increasing with area (Figure 8). Evidence from Figure 9 and T test of mean flow pathway length per unit area shows that the NFM benefit of MCUG was marginal over smaller spatial extents than 1225 m². Therefore, larger areas of MCUG would likely be needed to deliver significant hydrological benefits via increased flowpath lengths over LPIG. Culm grassland, which includes tussocks of *M. caerulea*, is currently being restored...
across fragmented areas of grassland in the South West of the UK, with a stated goal of increasing water storage and attenuation in restored fields (Devon Wildlife Trust, 2014). At present, areas of unimproved grassland are often over very limited extents (<2000 m², i.e., small fields) and fragmented (Blakesley & Buckley, 2016; Devon Wildlife Trust, 2014). This research highlights that more extensive areas should be restored if NFM goals are to be achieved, particularly as at present, fields of Culm grassland are highly fragmented with no landscape connectivity and thus less chance to impose more hydrological disconnectivity. The fragmentation of wetlands reducing their potential hydrological benefits has been highlighted globally, such as China and the USA (Johnson et al., 2014; Liu et al., 2020). Results here suggest that restoring wetlands or unimproved grasslands for hydrological reasons (e.g., reducing hydrological connectivity) needs to be done on spatial extents exceeding at least 1225 m².

The hydrological impact of microtopographic features such as tussocks acting over large areas >1225 m² can deliver important functional shifts within catchment systems (Antoine et al., 2009; Phillips, 1988). Phillips (1988) states that geomorphic systems are characterised by complex process interactions at multiple scales, of which microtopography can be one such influence upon hydrological processes such as infiltration and overland flow pathways, but often with limited understanding. Dunne et al. (1991) argues that infiltration rates on grassland slopes vary with the interaction of rainfall, run-off and vegetation topography because microtopography increases the surface area over which infiltration can occur. The importance of microtopography in controlling connectivity that results in NFM benefits is not widely quantified, particularly in grasslands, even though some analogous environments have been studied. For example, Courtwright and Findlay (2011) found microtopographic indentations in the tidal swamp of the Hudson River created areas of water storage which altered the basin's storage capacity. The duplication of the mounds and pooling in forested wetlands was used by Barry et al. (1996) to restore wetland properties of water storage according to a similar mechanism observed here in M. caerulea-dominated unimproved grassland. Appels et al. (2011) similarly found that microtopographic depressions in agricultural fields disrupted connectivity and increased infiltration at the field scale. Although our work has studied just one field of MCUG and one control field comprising LPiG, these fields are both typical of MCUG and LPiG fields of North Devon and the wider UK. These similarities include seasonally saturated soils typical of wetlands, low field slopes (<5°) and similar vegetation dominance such as tussocks or L. perenne. We have shown that grassland structure can influence drainage density and thus hydrological connectivity. We have used GIS-based models to show that flow pathways and drainage density are impacted by the presence of microtopographic structures caused by tussock grasses.

Is SfM photogrammetry an effective method to assess complex surface structures?

Three different survey methods were deployed within this research: SfM photogrammetry, LiDAR and field assessment using a GNSS. SfM photogrammetry provided the finest spatial resolution product with which to assess differences in microtopography and subsequently to quantify potential impact upon connectivity between unimproved and improved grassland. LiDAR is a common data source for hydrological modelling, with resolution up to 0.25 m possible in the UK to deliver high resolution catchment assessments (England & Gurnell, 2016; Vierling et al., 2008). The LiDAR DSM used for analysis in this study had a relatively high resolution at 1 m, a size which has been used to assess wetland connectivity, such as Wu and Lane’s (2017) assessment of wetland depression ability to disconnect flow pathways. Nonetheless, we found that this spatial grain is inadequate to capture the fine microtopography present in unimproved tussock grasslands which clearly influence field connectivity (Figures 7 and 9). Previous studies have also highlighted this issue. For instance, in a comparison of 1- and 10-m resolution LiDAR Zhao et al. (2010) noted that even 1-m LiDAR was insufficient to capture soil conservation structures such as diversion terraces, which may have resulted in missing vital flow pathway disruption. In comparison to LiDAR, SfM photogrammetry was more than adequate to assess tussock structure and model flow processes, though clearly data acquisition over large areas, comparable to LiDAR coverage would present an additional challenge.

The use of a GNSS to survey points manually to form a DSM could be considered an alternative method to LiDAR, particularly when greater accuracy in three dimensions is needed. For example, Higgitt and Warburton (1999) and Nuimura et al. (2012) both used GNSS to assess meander changes in remote upland areas that lacked fine-spatial resolution LiDAR. The GNSS in this study provided accurate XY points from which to build a DSM through kriging (Figure 5), but a point density of 38.44 points per m² was insufficient to capture the tussock outline in comparison to SfM photogrammetry. The mean z error of -0.11 m may reflect average vegetation height upon the tussocks as they regrew, as the GNSS rover recorded tussock height from soil mass, not from small amount of grass height upon the tussock which had grown after swaling. In contrast, a UAV DPC will incorporate grass upon the tussock as tussock structure. This error is minor when the tussock structure was still clearly captured. The UAV survey had 1493 points per m² which was more than adequate to capture the structures in detail for hydrological analysis. SfM photogrammetry to assess vegetation structures has already been proven as a strong method in ecology, such as for vegetation surveys and biomass quantification (Cunliffe et al., 2016; Dandois & Ellis, 2010; Puliti et al., 2015) and is being explored as a method to assess fluvial features (Debell et al., 2016; Woodget et al., 2015).

5 | CONCLUSION

Unimproved grasslands with microtopographic tussock structures of M. caerulea can play an important role in reducing overland flow impacts when compared to improved grasslands. The lower connectivity of these environments may reduce overland flow by storing and delaying run-off to rivers. The potential benefits of disconnectivity have been shown to increase with area, making a case for restoring
unimproved grasslands on a large scale. The benefits of unimproved grassland for flow attenuation can be used widely through the restoration of sites that are currently improved grassland.

The use of SfM photogrammetry to assess connectivity was highly effective for grasslands when compared to traditional methods of both LiDAR and manual surveys using a GNSS. The use of UAVs in NFM should therefore be considered as a method to assess field-scale structure and function for vegetation with limited understanding, such as those within unimproved grasslands. This understanding can then be used to understand the impact of field connectivity across a catchment, adapting roughness coefficients and field properties accordingly within models. This study also demonstrates the importance of not treating grasslands as one homogenous unit in hydrological modelling, and parameters such as roughness coefficients should be adjusted by researchers accordingly. The potential of SfM photogrammetry to assess unimproved grassland with complex microtopography such as _M. caerulea_ tussocks is substantial.

**ACKNOWLEDGEMENTS**

We thank our reviewer Professor Andy Baird whose comments helped improve and clarify this manuscript. We would also like to thank the multiple colleagues who supported fieldwork. We acknowledge funding support from the Environment Agency, Devon Wildlife Trust, INTERREG project (Climate resilient community-based catchment planning and management) Triple-C and the University of Exeter.

**CONFLICT OF INTEREST**

The authors have no conflict of interest to declare.

**DATA AVAILABILITY STATEMENT**

The data that support the findings of this study are available at DOI, with code available online (at [https://github.com/exeter-creww/Ellis_et_al_2021_supporting_information](https://github.com/exeter-creww/Ellis_et_al_2021_supporting_information)).

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**REFERENCES**

Antoine, M., Javaux, M., & Bielders, C. (2009). What indicators can capture runoff-relevant connectivity properties of the micro-topography at the plot scale? *Advances in Water Resources*, 32(8), 1297–1310. [https://doi.org/10.1016/j.advwatres.2009.05.006](https://doi.org/10.1016/j.advwatres.2009.05.006)

Appels, W. M., Bogaart, P. W., & van der Zee, S. E. A. T. M. (2011). Influence of spatial variations of microtopography and infiltration on surface runoff and field scale hydrological connectivity. *Advances in Water Resources*, 34(2), 303–313. [https://doi.org/10.1016/j.advwatres.2010.12.003](https://doi.org/10.1016/j.advwatres.2010.12.003)

Bakker, M., & Lane, S. N. (2017). Archival photogrammetric analysis of river-floodplain systems using structure from motion (SFM) methods. *Earth Surface Processes and Landforms*, 42(8), 1274–1286. [https://doi.org/10.1002/esp.4085](https://doi.org/10.1002/esp.4085)

Barber, C. P., & Shortridge, A. (2013). Lidar elevation data for surface hydrologic modeling: Resolution and representation issues. *Cartography and Geographic Information Science*, 32(4), 401–410. [https://doi.org/10.1559/152304005775194692](https://doi.org/10.1559/152304005775194692)

Barry, W. J., Garlo, A. S., & Wood, C. A. (1996). Duplicating the mound-and-pool microtopography of forested wetlands. *Restoration & Management Notes*, 14, 15–21.

Bater, C. W., & Coops, N. C. (2009). Evaluating error associated with Lidar-derived DEM interpolation. *Computers and Geosciences*, 35(2), 289–300. [https://doi.org/10.1016/j.cageo.2008.09.001](https://doi.org/10.1016/j.cageo.2008.09.001)

Bilotta, G. S., & Brazier, R. E. (2008). Understanding the influence of suspended solids on water quality and aquatic biota. *Water Research*, 42(12), 2849–2861. [https://doi.org/10.1016/j.watres.2006.03.018](https://doi.org/10.1016/j.watres.2006.03.018)

Bilotta, G. S., Brazier, R. E., Haygarth, P. M., Macleod, C. J. A., Butler, P., Granger, S., Krueger, T., Freer, J., & Quinton, J. (2008). Rethinking the contribution of drained and undrained grasslands to sediment-related water quality problems. *Journal of Environmental Quality*, 37(3), 906–914. [https://doi.org/10.2134/jeq2007.0457](https://doi.org/10.2134/jeq2007.0457)

Blakesley, D., & Buckley, P. (2016). *Grassland restoration and management*. Exeter, UK: Pelagic Publishing.

Bond, S., Kirkby, M. J., Johnston, J., Crowle, A., & Holden, J. (2020). Seasonal vegetation and management influence overland flow velocity and roughness in upland grasslands. *Hydrological Processes*, 34(18), 3777–3791. [https://doi.org/10.1002/hyp.13842](https://doi.org/10.1002/hyp.13842)

Bracken, L. J., & Croke, J. (2007). The concept of hydrological connectivity and its contribution to understanding runoff-dominated geomorphic systems. *Hydrological Processes*, 21(13), 1749–1763. [https://doi.org/10.1002/hyp.6313](https://doi.org/10.1002/hyp.6313)

Bracken, L. J., Wainwright, J., Ali, G. A., Tetzlaff, D., Smith, M. W., Reaney, S. M., & Roy, A. G. (2013). Concepts of hydrological connectivity: Research approaches, pathways and future agendas. *Earth-Science Reviews*, 119, 17–34. [https://doi.org/10.1016/J.EARSCIREV.2013.02.001](https://doi.org/10.1016/J.EARSCIREV.2013.02.001)

Brazier, R. E., Bilotta, G. S., & Haygarth, P. M. (2007). A perspective on the role of lowland, agricultural grasslands in contributing to erosion and water quality problems in the UK. *Earth Surface Processes and Landforms*, 32(6), 964–967. [https://doi.org/10.1002/esp.1484](https://doi.org/10.1002/esp.1484)

Bullock, J. M., Jefferson, R. G., Blackstock, T. H., Pakeman, R. J., Emmett, B. A., & Pywell, R. J. (2011). Semi-natural grasslands. In UK National Ecosystem Assessment: Technical report (pp. 161–195). Cambridge: UNEP-WCMC.

Burgess-Gamble, L., Ngai, R., Wilkinson, M., Nisbet, T., Pontee, N., Harvey, R., Kipling, K., Addy, S., Rose, S., Maslen, S., Jay, H., Nicholson, A., Page, T., Jonczyk, J., & Quinn, P. (2017). Working with natural processes—Evidence directory. Bristol: Environment Agency.

Cammeraat, L. H., & Imeson, A. C. (1999). The evolution and significance of soil-vegetation patterns following land abandonment and fire in Spain. *Catena*, 37(1–2), 107–127. [https://doi.org/10.1016/S0008-7332(98)00072-1](https://doi.org/10.1016/S0008-7332(98)00072-1)

Chow, V. T. (1959). *Open-channel hydraulics*. New York: McGraw-Hill Book Co.

Collins, A. L., Zhang, Y., McChesney, D., Walling, D. E., Haley, S. M., & Smith, P. (2012). Sediment source tracing in a lowland agricultural catchment in southern England using a modified procedure combining statistical analysis and numerical Modelling. *Science of the Total Environment*, 414, 301–317. [https://doi.org/10.1016/j.scitotenv.2011.10.062](https://doi.org/10.1016/j.scitotenv.2011.10.062)

Courtwright, J., & Findlay, S. E. G. (2011). Effects of microtopography on hydrology, Physicochemistry, and vegetation in a tidal swamp of the Hudson River. *Wetlands*, 31, 239–249. [https://doi.org/10.1007/s13157-011-0156-9](https://doi.org/10.1007/s13157-011-0156-9)

Cunliffe, A. M., Brazier, R. E., & Anderson, K. (2016). Ultra-fine grain landscape-scale quantification of Dryland vegetation structure with drone-acquired structure-from-motion photogrammetry. *Remote Sensing of Environment*, 183, 129–143. [https://doi.org/10.1016/j.rse.2016.05.019](https://doi.org/10.1016/j.rse.2016.05.019)

Dadson, S., Hall, J., Murgatroyd, A., Acreman, M., Bates, P., Beven, K., Heathwaite, L., Holden, J., Holman, I., Lane, S., O’Connell, E., Penning-Rossell, P., Reynard, N., Sear, D., Thorne, C., & Wilby, R. (2017). A
restatement of the natural science evidence concerning catchment-based ‘natural’ flood management in the UK. *Proceedings of the Royal Society, 473*, 1–34.

Dandois, J., Baker, M., Olano, M., Parker, G., & Ellis, E. (2017). What is the point? Evaluating the structure, color, and semantic traits of computer vision point clouds of vegetation. *Remote Sensing, 9*(4), 355. https://doi.org/10.3390/rs9040355

Dandois, J. P., & Ellis, E. C. (2010). Remote sensing of vegetation structure using computer vision. *Remote Sensing, 2*(4), 1157–1176. https://doi.org/10.3390/rs2041157

Dandois, J. P., Olano, M., Ellis, E. C., Baghdadi, N., Kerle, N., & Thenkabail, P. S. (2015). Optimal altitude, overlap, and weather conditions for computer vision UAV estimates of forest structure. *Remote Sensing, 7*, 13895–13920. https://doi.org/10.3390/rs71013895

Debell, L., Anderson, K., Brazier, R. E., King, N., & Jones, L. (2016). Water resource management at catchment scales using lightweight UAVs: Current capabilities and future perspectives. *Journal of Unmanned Vehicle Systems, 41*(18), 7–30. https://doi.org/10.1139/juvs-2015-0026

DEFRA. (2012). *Agriculture in the United Kingdom*. United Kingdom: Department of Environment, Food and Rural Affairs.

Devon Wildlife Trust. 2014. Culm grassland: An assessment of recent historic change.

Dixon, M. D., Boever, C. J., Danzeisen, V. L., Merkord, C. L., Munes, E. C., Scott, M. L., Carter Johnson, W., & Cowman, T. C. (2015). Effects of a ‘natural’ flood event on the riparian ecosystem of a regulated large-river system: The 2011 flood on the Missouri River, USA. *Ecohydrology, 8*(5), 812–824. https://doi.org/10.1002/eco.1613

Dunne, T., Zhang, W., & Aubry, B. F. (1991). Effects of rainfall, vegetation, and microtopography on infiltration and runoff. *Water Resources Research, 27*(9), 2271–2285. https://doi.org/10.1029/91WR01585

Ellis, N., Anderson, K., & Brazier, R. (2021). Mainstreaming natural flood management: A proposed research framework derived from a critical evaluation of current knowledge. *Progress in Physical Geography: Earth and Environment*. https://doi.org/10.1177/0309133321997299

England, J., & Gurnell, A. M. (2016). Incorporating catchment to reach scale. *Dunne, T., Zhang, W., & Aubry, B. F. (1991). Effects of rainfall, vegetation, and microtopography on infiltration and runoff. Water Resources Research, 27*(9), 2271–2285. https://doi.org/10.1029/91WR01585

Engel, S., Ziegler, T., & Nadelhoffer, K. J. (2009). Forests and the carbon cycle. *Science, 326*(5953), 993–998. https://doi.org/10.1126/science.1174825

Fawcett, D., Azlan, B., Hill, T. C., Kho, L. K., Bennie, J., & Anderson, K. (2019). Unmanned aerial vehicle (UAV) derived structure-from-motion photogrammetry point clouds for oil palm (Elaeis Guineensis) canopy segmentation and height estimation. *International Journal of Remote Sensing, 40*(19), 7538–7560. https://doi.org/10.1080/01431161.2019.1591651

Fraser, R. H., Olthof, I., Lantz, T. C., Carla, S., Fraser, R. H., Olthof, I., & Schmitt, C. (2016). UAV photogrammetry for mapping vegetation in the low-Arctic. *Arctic Science, 2*, 79–102. doi:10.1139/as-2016-0008

Glendell, M., McShane, G., Farrow, L., James, M. R., Quinton, J., Anderson, K., Evans, M., Benaud, P., Rawlins, B., Morgan, D., Lee, J., Kirkham, M., DeBell, L., Quine, T. A., Lark, M., Rickson, J., & Brazier, R. E. (2017). Testing the utility of structure-from-motion photogrammetry reconstructions using small unmanned aerial vehicles and ground photography to estimate the extent of upland soil erosion. *Earth Surface Processes and Landforms, 42*(12), 1860–1871. https://doi.org/10.1002/esp.4142

Godsey, S. E., & Kirchner, J. W. (2014). Dynamic, discontinuous stream networks: Hydrologically driven variations in active drainage density, flowing channels and stream order. *Hydrological Processes, 28*(23), 5791–5803. https://doi.org/10.1002/hyp.10310

Hansen, J. R., Refsgaard, J. C., Hansen, S., & Ernstsen, V. (2007). Problems with heterogeneity in physically based agricultural catchment models. *Journal of Hydrology, 342*(1–2), 1–16. https://doi.org/10.1016/j.jhydrol.2007.04.016

Higgit, D. L., & Warburton, J. (1999). Applications of differential GPS in upland fluvial geomorphology. *Geomorphology, 29*(1–2), 121–134. https://doi.org/10.1016/S0169-555X(99)00010-0

Holden, J., Kirkby, M. J., Lane, S. N., Milledge, D. G., Brookes, C. J., Holden, V., & Mcdonald, A. T. (2008). Overland flow velocity and roughness properties in Peatlands. *Water Resources Research, 44*, 6415–6426. https://doi.org/10.1029/2007WR006052

Holden, J., Haygarth, P., MacDonald, J., Jenkins, A., Spaets, A., Orr, H., Dunn, N., Harris, B., Pearson, P., McGonigle, D., Humble, A., Ross, M., Harris, J., Meacham, T., Benton, T., Staines, A., & Noble, A. (2014). Agriculture’s impacts on water quality. *Global Water Security, 4*(2), 1–24.

James, M., Robson, S., D’Oleire-Oltmanns, S., & Nietherammer, U. (2017). Optimising UAV topographic surveys processed with structure-from-motion: Ground control quality, quantity and bundle adjustment. *Geomorphology, 280*, 51–66. https://doi.org/10.1016/j.geomorph.2016.11.021

James, M. R., & Robson, S. (2014). Mitigating systematic error in topographic models derived from UAV and ground-based image networks. *Earth Surface Processes and Landforms, 39*(10), 1413–1420. https://doi.org/10.1002/esp.3609

Jaud, M., Passot, S., Le Bivic, R., Delacourt, C., Grandjean, P., & Le Dantec, N. (2016). Assessing the accuracy of high resolution digital surface models computed by PhotoScan® and MicMac® in sub-optimal survey conditions. *Remote Sensing, 8*(6), 465. https://doi.org/10.3390/rs8060465

Javernick, L., Brasington, J., & Caruso, B. (2014). Modeling the topography of shallow braided Rivers using structure-from-motion photogrammetry. *Geomorphology, 213*, 166–182. https://doi.org/10.1016/j.geomorph.2014.01.006

Jenkins, D. G., & McCauley, L. A. (2006). GIS, SINKS, FILL, and disappearing wetlands: unintended consequences in algorithm development and use. In *Association for Computing Machinery (ACM)* (pp. 277-282). New York: Association for Computing Machinery.

Johnson, Y. B., Shear, T. H., & James, A. L. (2014). Novel ways to assess forested wetland restoration in North Carolina using Ecological hydrological patterns from reference sites. *Ecology, 7*(2), 692–702. https://doi.org/10.1002/eco.1390

Laidlaw, A. S., & Frame, J. (2013). Improved grassland management. *Crowood: Marlborough.*

Liu, D., Wang, X., Aminjafari, S., Yang, W., Cui, B., Yan, S., Zhang, Y., Zhu, J., & Jaramillo, F. (2020). Using InSAR to identify hydrological connectivity and barriers in a highly-fragmented wetland. *Hydrological Processes, 34*(23), 4417–4430. https://doi.org/10.1002/hyp.13899

López-Vicente, M., & Álvarez, S. (2018). Influence of DEM resolution on Modelling hydrological connectivity in a complex agricultural catchment with Woody crops. *Earth Surface Processes and Landforms, 43*(7), 1403–1415. https://doi.org/10.1002/esp.4321

Ludwig, J. A., Wilcox, B. P., Breshears, D. D., Tongway, D. J., & Imeson, A. C. (2005). Vegetation patches and runoff-erosion as interacting ecohydrological processes in semiarid landscapes. In *Ecology (Vol. 86)* (pp. 288–297). Ecological Society of America.

Luscombe, D. J., Anderson, K., Gatis, N., Grand-Clement, E., & Brazier, R. E. (2015). Using airborne thermal imaging data to measure near-surface hydrology in upland ecosystems. *Hydrological Processes, 29*(6), 1656–1668. https://doi.org/10.1002/hyp.10285

McIntyre, N., & Marshall, M. (2010). Identification of rural land management signals in runoff response. *Hydrological Processes, 24*(24), 3521–3534. https://doi.org/10.1002/hyp.7774

Milan, D. J., Heritage, G. L., & Hetherington, D. (2007). Application of a 3D laser scanner in the assessment of erosion and deposition volumes
and channel change in a proglacial river. In Earth surface processes and landforms (Vol. 32) (pp. 1657–1674). John Wiley and Sons Ltd.

Nuimura, T., Fujita, K., Yamaguchi, S., & Sharma, R. R. (2012). Elevation changes of glaciers revealed by multitemporal digital elevation models calibrated by GPS survey in the Khumbu region, Nepal Himalaya, 1992-2008. Journal of Glaciology, 58(210), 648–656. https://doi.org/10.3189/2012JoG11J061

Odoni, N. A., Nisbet, T. R., Broadmeadow, S. B., Lane, S. N., Huxford, L. V., Pacey, J., & Marrington, S. (2010). Evaluating the Effects of Riparian Woodland and Large Woody Debris Dams on Peak Flows in Pickering Beck, North Yorkshire. In Proceedings of the flood and coastal management 2010 Conference, The International Centre, Telford (Vol. 29). Telford: The International Centre.

Papnicolaou, A. N., Abban, B. K. B., Dermisis, D. C., Giannopoulos, C. P., Flanagan, D. C., Frankenberger, J. R., & Wach, K. M. (2018). Flow resistance interactions on hillslopes with heterogeneous attributes: Effects on runoff hydrograph characteristics. Water Resources Research, 54(1), 359–380. https://doi.org/10.1002/2017WR021109

Pareto, K., & Pareto, U. (2012). Quantitative geomorphological analysis of a watershed of Ravi River basin, H.P. India. International Journal of Remote Sensing and GIS, 1(1), 41–56.

Peyraud, J. L., van der Pol-van Dasselaar, A., Collins, P., Huguenin-Elie, O., Dillon, P., & Peeters, A. (2014). MultiSward multi-species swards and multi-scale strategies for multifunctional Grassland-Base ruminant production systems. EGF at 50: The Future of European Grasslands, 19, 695–715.

Phillips, J. D. (1988). The role of spatial scale in geomorphic systems. Geographical Analysis, 20(4), 308–317. https://doi.org/10.1111/j.1538-4632.1988.tb00185.x

Pligin, E. S., Macleod, C. J. A., Blackwell, M. S. A., Bol, R., Hogan, D. V., Chadwick, D. R., Cardenas, L., Misselbrook, T. H., Haygarth, P. M., & Brazier, R. E. (2010). Interactions among agricultural production and other ecosystem services delivered from European temperate grassland. Advances in Agronomy, 109, 117–154. https://doi.org/10.1016/B978-0-12-385040-9.00004-9

Pretty, J. N., Brett, C., Gee, D., Hine, R. E., Mason, C. F., Morison, J. I. L., Raven, H., Rayment, M. D., & van der Bijl, G. (2000). An assessment of the Total external costs of UK agriculture. Agricultural Systems, 65(2), 113–136. https://doi.org/10.1016/S0308-521X(00)00031-7

Pulliiti, S., Örka, H., Gabakken, T., & Næsset, E. (2015). Inventory of small forest areas using an unmanned aerial system. Remote Sensing, 7(8), 9632–9654. https://doi.org/10.3390/rs70809632

Puttock, A., & Brazier, R. (2014). Culm grasslands proof of concept study phase 1: Developing an understanding of the hydrolotry, water quality and soil resources of unimproved. Exeter: Grasslands.

Quinn, P., & Wilkinson, M. (2019). Runoff attenuation features: A nature based solution for flood and water pollution management. Geophysical Research Abstracts, 21, 1–1.

Quinton, W. L., & Carey, S. K. (2008). Towards an energy-based runoff generation theory for tundra landscapes. Hydrological Processes, 22(23), 4649–4653. https://doi.org/10.1002/hyp.7164

Roussel, J. R., Huty, D., De Boisseni, F., & Meador A. S. (2019). LiDAR package R: Airborne LiDAR data manipulation and visualization for forestry applications.

Sanz-Abelaneto, E., Chandler, J., Rodriguez-Pérez, J., & Ordóñez, C. (2018). Accuracy of unmanned aerial vehicle (UAV) and SFM photogrammetry survey as a function of the number and location of ground control points used. Remote Sensing, 10(10), 1606. https://doi.org/10.3390/rs10101606

Shepard, M. K., Campbell, B. A., Bulmer, M. H., Farr, T. G., Gaddis, L. R., & Pflaut, J. J. (2001). The roughness of natural terrain: A planetary and remote sensing perspective. Journal of Geophysical Research: Planets, 106(E12), 32777–32795. https://doi.org/10.1029/2000JE001429

Smith, M. W., Carrivick, J. L., & Quincey, D. J. (2016). Structure from motion photogrammetry in physical geography. Progress in Physical Geography: Earth and Environment, 40(2), 247–275. https://doi.org/10.1177/03091331565805

Soille, P. (2004). Optimal removal of spurious pits in grid digital elevation models. Water Resources Research, 40(12), 1–9. https://doi.org/10.1029/2004WR003060

Taylor, K., Rowland, A. P., & Jones, H. E. (2001). Molinia Caerulea (L) Moench. Journal of Ecology, 89(1), 126–144. https://doi.org/10.1046/j.1365-2745.2001.00534.x

Thomas, H., & Nisbet, T. R. (2007). An assessment of the impact of floodplain woodland on flood flows. Water and Environment Journal, 21(2), 114–126. https://doi.org/10.1111/j.1747-6593.2006.00056.x

Tonkin, T., & Midgley, N. (2016). Ground-control networks for image based surface reconstruction: An investigation of optimum survey designs using UAS derived imagery and structure-from-motion photogrammetry. Remote Sensing, 8(9), 786. https://doi.org/10.3390/rs8090786

Torres-Sánchez, J., López-Granados, F., Borra-Serrano, I., & Peña, J. M. (2018). Assessing UAS-collected image overlap influence on computation time and digital surface model accuracy in olive orchards. Precision Agriculture, 19(1), 115–133. https://doi.org/10.1007/s11119-017-9502-0

Venticinque, E., Forsberg, B., Barthem, R., Petry, P., Hess, L., Mercado, A., Cañas, C., Montoya, M., Durán, C., & Goulding, M. (2016). An explicit GIS-Based River basin framework for aquatic ecosystem conservation in the Amazon. Earth System Science Datas, 8(2), 651–661. https://doi.org/10.5194/essd-8-651-2016

Vierling, K., Vierling, L., Gould, W., Martinuzzi, S., & Clawges, R. (2008). Lidar: Shedding new light on habitat characterization and modeling. Frontiers in Ecology and Environment, 6(2), 90–98. https://doi.org/10.1890/070001

Wallace, E. E., & Chappell, N. A. (2020). A statistical comparison of Spatio-temporal surface moisture patterns beneath a semi-natural grassland and permanent pasture: From drought to saturation. Hydrological Processes, 34(13), 3000–3020. https://doi.org/10.1002/hyp.13774

Werner, K. J., & Zedler, J. B. (2002). How sedge meadow soils, microtopography, and vegetation respond to sedimentation. Wetlands, 22(3), 451–466. https://doi.org/10.1672/0277-5212(2002)022%5B451:HSMSSMA%5D2.0.CO;2

Woodget, A. S., Carbonneau, P. E., Visser, F., & Maddock, I. P. (2015). Quantifying submerged fluvial topography using Hyperspatial resolution UAV imagery and structure from motion photogrammetry. Earth Surface Processes and Landforms, 40(1), 47–64. https://doi.org/10.1002/esp.3613

Wu, Q., & Lane, C. R. (2017). Delineating wetland catchments and modeling hydrologic connectivity using Lidar data and aerial imagery. Hydrology and Earth System Sciences, 21(7), 3579–3595. https://doi.org/10.5194/hess-21-3579-2017

Zhao, Z., Benoy, G., Thien, L. C., Rees, H. W., Daigle, J.-L., & Meng, F.-R. (2010). Impacts of accuracy and resolution of conventional and LiDAR based DEMs on parameters used in hydrologic modeling. Water Resources Management, 24, 1363–1380. https://doi.org/10.1007/s11269-009-9503-5

SUPPORTING INFORMATION
Additional supporting information may be found online in the Supporting Information section at the end of this article.

How to cite this article: Ellis, N., Brazier, R., & Anderson, K. (2021). Comparing fine-scale structural and hydrologic connectivity within unimproved and improved grassland. Ecohydrology, 14(7), e2330. https://doi.org/10.1002/eco.2330