Temporal variation in suspended sediment transport: linking sediment sources and hydro-meteorological drivers

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ABSTRACT: Suspended sediment concentrations (SSCs) in rivers are variable in time due to interacting soil erosion and sediment transport processes. While many hydro-meteorological variables are correlated to SSCs, interpretation of these correlations in terms of driving processes requires in-depth knowledge of the catchment. Detailed sediment source information is needed to establish the causal linkages between driving processes and variations in SSC. This study innovatively combined sediment fingerprinting with multivariate statistical analyses of hydro-meteorological data to investigate how differential contributions of sediment sources control SSC in response to hydro-meteorological variables during high-flow events in rivers. Applied to the River Aire (UK), five sediment sources were classified: grassland topsoil in three lithological areas (limestone, millstone grit and coal measures), eroding riverbanks, and street dust. A total of 159 suspended sediment samples were collected during 14 high-flow events (2015–2017). Results show substantial variation in sediment sources during high-flow events. Limestone grassland and street dust, the dominant contributors to the suspended sediment, show temporal variations consistent with variations in total SSC, and are correlated with precipitation and discharge shortly prior and during high-flow events (i.e. fast mobilization to and within river). Contrarily, contributions from millstone and coals grassland appear to be driven by antecedent hydro-meteorological conditions (i.e. lag-time between soil erosion and sediment delivery). Riverbank material is poorly correlated to hydro-meteorological variables, possibly due to weak source discrimination or the infrequent nature of its delivery to the channel. Differences in source-specific drivers and process interactions for sediment transport demonstrate the difficulty in generalizing sediment transport patterns and developing targeted suspended sediment management strategies. While more research is essential to address different uncertainties emerging from the approach, the study demonstrates how empirical data on sediment monitoring, fingerprinting, and hydro-meteorology can be combined and analysed to better understand sediment connectivity and the factors controlling SSC. © 2019 John Wiley & Sons, Ltd.

KEYWORDS: sediment fingerprinting; DRIFTS; hysteresis; sediment connectivity

Introduction

Natural suspended sediment (SS) transport dynamics in rivers are often strongly disturbed, especially when the degree of human intervention in a river catchment is high (Walling et al., 2003b; Taylor and Owens, 2009; Lexartza-Artza and Wainwright, 2011; Wohl, 2015), leading to problems such as excessive siltation, pollution, and ecosystem degradation (Bilotta and Brazier, 2008; Mauad et al., 2015). Sustainable management solutions require a comprehensive understanding of catchment erosion and sediment transport dynamics (Owens et al., 2005). However, high spatiotemporal variability in SS transport complicates our ability to quantify SS concentrations (SSCs) and sources over multiple timescales (Bilotta et al., 2012; Vercruysse et al., 2017).

Past research has identified a range of hydro-meteorological variables (e.g. discharge, antecedent soil moisture conditions, rainfall intensity and duration, and air temperature) to explain (and predict) variations in SSC (Onderka et al., 2012; Zimmermann et al., 2012; Francke et al., 2014; Tena et al., 2014; Perks et al., 2015; Zeiger and Hubbart, 2016). However, variation in SSC is also driven by short- and long-term changes in sediment sources due to exhaustion in sediment supply, vegetation changes, mass movements, or human landscape disturbances (e.g. land-cover change or dam construction) (Belmont et al., 2011; Rovira et al., 2015; Grabowski and Gurnell, 2016; Vanmaercke et al., 2017). These changes in sediment sources are only included implicitly into correlations between SSC with hydro-meteorological variables, which therefore only offer a partial explanation for the spatiotemporal variation in SS transport without actual information on the continuum of SS sources and transfer across the catchment (Bracken et al., 2015).

For example, the most commonly used hydro-meteorological explanatory variable for SSC is river
discharge, and temporal variations (i.e. hysteresis patterns) in the sediment ratings curve (i.e. relationship between river discharge and SSC) are frequently used to extrapolate information about processes controlling SS availability, transport and sources (e.g. Williams, 1989; Francke et al., 2008; Smith and Dragovich, 2009; Eder et al., 2010; Aich et al., 2014; Pietroš et al., 2015; Sun et al., 2015; Lloyd et al., 2016; Sher riff et al., 2016). A clockwise hysteresis pattern during a high-flow event (i.e. when the peak SSC precedes the peak discharge) is typically attributed to contribution of sediment sources located close the river (Eder et al., 2010; Aich et al., 2014). Conversely, a counter-clockwise pattern, characterized by a delayed peak SSC relative to discharge, is attributed generally to contribution of more distant sediment sources becoming connected to the river system (Fan et al., 2012; Francke et al., 2014; Tena et al., 2014; Fang et al., 2015; De Girolamo et al., 2015). However, interpretation of hysteresis patterns in terms of processes and sediment sources strongly depends on the study site; similar variations in SSC can be the result of changes in the total sediment supply (e.g. exhaustion of all sediment sources) or changes in a sediment source (e.g. river bank collapse), which can only be determined by in-depth knowledge of the catchment (Smith and Dragovich, 2009; Vercruysse et al., 2017).

To improve the scientific understanding of the process interactions controlling SSC in rivers, empirical and analytical approaches are needed that differentiate sediment sources, quantify their contribution to the total SSC, and link them to hydro-meteorological drivers (Fryirs, 2013). In other words, alongside quantification of the amount and timing of SS transport in rivers, there is a need for scientific data on sources of SS and how it changes over time, during and between high-flow events and over longer time spans.

To this end, many studies have investigated SS sources through sediment fingerprinting (e.g. Franz et al., 2014; Palazón et al., 2015; Chen et al., 2016; Vale et al., 2016; Tiecher et al., 2017), which has evolved significantly over the past decades as a method to estimate sediment source contributions directly from river sediment (Davis and Fox, 2009; Mukundan et al., 2012; Owens et al., 2016; Pulley and Collins, 2018). Particularly interesting from a monitoring perspective is the recent development of methods based on infrared spectrometry (Poulenard et al., 2009; Cooper et al., 2015; Tiecher et al., 2017), which are more time- and cost-effective compared to traditional geochemical sediment fingerprinting methods (Collins et al., 2017). These advancements enable sediment fingerprinting to be easier applied at a finer temporal frequency (i.e. event scale) to retrieve detailed information on variations in SS sources.

Especially with the growing availability of detailed monitoring data in river catchments (e.g. discharge and precipitation), opportunities emerge to combine SS monitoring with sediment fingerprinting and multivariate analyses at fine temporal resolutions. Therefore, this study innovatively combines SS data with sediment fingerprinting and hydro-meteorological information to investigate how differential contributions of sediment sources control total SSCs in response to hydro-meteorological variables during high-flow events in rivers. Diffuse Reflectance Infrared Fourier Transform spectrometry (DRIFTS)-based sediment fingerprinting is applied on an extensive SSC dataset for the River Aire (UK) and combined with multivariate analyses of detailed hydro-meteorological data to identify controlling factors and processes for source-specific SS transport dynamics. Better insights into these factors will help the development of source-specific erosion and sediment transport models, and guide targeted soil conservation and pollution prevention strategies (Owens et al., 2005; SedNet, 2009; Perks et al., 2017).

Materials and Methods

Study area

The total catchment area of the River Aire is 879 km², with an area of 690 km² upstream of the point of SS sampling in the City of Leeds. Between 1989 and 2017 the mean annual rainfall was 1018 mm yr⁻¹, and the mean discharge 15 m³ s⁻¹. Based on random monthly SS measurements (i.e. manual samples taken on a random day each month) from the Environment Agency (EA) of England (1990–2014), the mean SSC in the River Aire within the city centre of Leeds is 15.8 mg l⁻¹ (range: 0–100 mg l⁻¹). The median absolute particle size of the SS ranges between 5.2 and 13.3 μm (Walling et al., 2003a; Carter et al., 2006).

The dominant land use is grassland (59%), followed by urbanized area (25%). The remaining land is covered in moorland (12%), primarily found at higher elevations in the upper catchment, and scattered arable land (4%). The catchment consists mainly of poorly draining loamy and clayey soils, with raw oligo-fibrous peats, and stagnohumic and stagnogley soils in the upper part, and brown earths and pelo-stagnogley soils in the middle and lower parts (Carter et al., 2003). The geology of the catchment dates from the Carboniferous Period and consists of three main zones: Coal Measures (31%), Millstone Grit (46%), and limestone and shale formations (23%) (British Geological Survey, 2016) (Figure 1).

Suspended sediment and hydro-meteorological data

SS samples were collected with a depth-integrating SS sampler (type US DH-81) during individual high-flow events between June 2015 and March 2017. Due to the urban environment and frequent boat navigation at the sampling location, it was impossible to install an automated sampler in the river. Therefore, samples were collected manually during daylight hours before, during, and after rainfall events with a frequency between 30 minutes and two hours, informed by real-time updates on river levels (https://www.gaugemap.co.uk) to capture discharge peaks. Water samples were filtered on pre-weighted, quartz fibre filters and dried for two hours at 105°C (Cooper et al., 2015; Pulley et al., 2015). In total, 14 high-flow events were sampled (159 individual samples), covering a range of peak discharges (23–120 m³ s⁻¹) and peak SSCs (18–1000 mg l⁻¹) (Figure 1).

High-frequency (15-minute) discharge and precipitation measurements were obtained from the EA. Discharge measurements originate from a monitoring station at Armley located 3 km upstream of the SS sampling site. Precipitation data were obtained from rain gauges located at the upstream edge of each geological zone at Malham Tarn (MT), Thornton Reservoir (TR), and Proctor Heights (PH) (Figure 1).

Sediment source data

Based on land use in the River Aire catchment and a previous sediment fingerprinting study (Carter et al., 2003), five potential SS sources were classified: soil from grassland in three geological zones [limestone (‘L’), millstone grit (‘M’), and coal measures (‘C’)], eroding riverbanks (‘R’) and urban street dust (‘U’). An erosion map based on the Revised Universal Soil Loss Equation (RUSLE) was used as a guideline during sampling to target zones within the catchment that are most prone to soil erosion. A total of 117 sediment source samples were collected. At each soil sampling location three subsamples were collected.
taken within 1 m$^2$. Source materials from grassland topsoil (21 locations $\times$ 3 replicates) and subsoil from eroding channel banks (12 locations $\times$ 3 replicates) were collected using a trowel (Figure 1). The top 5 cm of the topsoil was sampled to ensure that only material likely to be eroded and transported to the river was collected (Carter et al., 2003; Martínez-Carreras et al., 2010; Cooper et al., 2015; Pulley et al., 2015). Street dust samples (18 samples) were collected along road drains using a dustpan and brush (Cooper et al., 2015; Pulley et al., 2015).

All sediment source samples were processed following the method developed by Poulenard et al. (2009). First, the samples were mixed with demineralized water and placed in a sonic bath for seven minutes to disaggregate clasts. Then the samples were wet sieved to retain the $<63$ μm fraction to reduce the effect of particle size variations on source attribution and spectral distortion (Poulenard et al., 2009; Laceby et al., 2017). Finally, all source samples were also filtered on quartz fibre filters and oven-dried for two hours at 105°C (Cooper et al., 2015; Pulley et al., 2015).

### Sediment fingerprinting

The DRIFTS-based sediment fingerprinting applied in this study is described in detail by Vercruysse and Grabowski (2018). In summary, the method consists of three main steps: (i) measuring SS and sediment source samples with DRIFTS; (ii) testing whether source samples can be discriminated from each other based on their DRIFTS spectra through a discriminant analysis; and (iii) developing source-specific partial least squares regression (PLSR) models based on DRIFTS spectra of experimental mixtures (54 mixtures; Vercruysse and Grabowski, 2018) with known source-quantities, which can subsequently be applied to estimate SS source contributions from DRIFTS spectra of SS.

The discriminant analysis demonstrated that urban street dust and material from grassland topsoil in the three lithological areas can be discriminated well based on their DRIFTS spectra, while riverbank has a lower degree of discriminatory power (Vercruysse and Grabowski, 2018). The difference in discriminatory power can be attributed to the primary origin of the sources. Riverbank material is generally a mixture of floodplain deposits consisting of various primary sediment sources, while street dust originates from distinctly different anthropogenic and natural sources (e.g., weathering of car tires, atmospheric deposition, road construction works) (Taylor and Owens, 2009; Vercruysse and Grabowski, 2018). The differences in discriminatory power are subsequently reflected in the uncertainty associated to the source-specific PLSR models, whereby the 95% confidence intervals range from ±10% for urban street dust and coals grassland, ±12–13% for limestone and millstone grassland, and ±18% for riverbank material (Table I, see also Supporting Information).

As the method is based on individual, source-specific PLSR models instead of a mass balance equation as in traditional sediment fingerprinting methods (Walling, 2013), the sum of all estimated source contributions is not set to 100%. In previous sediment fingerprinting studies using DRIFTS (Poulenard et al., 2009, 2012), a sum of these individually estimated contributions close to 100% was then considered an indication that all major sources were correctly identified. However, due to model uncertainties associated with the source-specific PLSR models, it is uncertain to what extent a deviation from 100% is caused by these uncertainties, by the sources included in the model, or by other factors such as particle size effects or other factors.

### Table 1. Partial least squares regression (PLSR) model statistics (CI: confidence interval).

| Model           | $R^2$ | 95% CI   |
|-----------------|-------|----------|
| Limestone PLSR  | 0.884 | ± 12%    |
| Millstone grit PLSR | 0.877 | ± 13%   |
| Coal PLSR       | 0.929 | ± 10%  |
| Riverbank PLSR  | 0.790 | ± 18%   |
| Urban street dust PLSR | 0.772 | ± 10%   |

Note: Adopted from Vercruysse and Grabowski (2018).
changes in the DRIFTS spectra over time (i.e. non-conservancy) (Laceby et al., 2017). To address the uncertainty related to the number of sources, Verbruggen and Grabowski (2018) performed a sensitivity analysis of the PLSR model results by omitting individual sources from the source classification. The results demonstrate that when an important source (in terms of contribution) is omitted, more contribution is attributed to the least well-discriminated source (i.e. riverbank material), while estimated contributions of well-discriminated sources remain constant. Estimated contributions from riverbanks are therefore highly uncertain, as additional (unclassified) sources might still be captured within this group. However, the analysis also suggests that the part represented by the riverbank samples is an important source; omitting the riverbank as a source impacts significantly on the estimated contributions of other sources (Verbruggen and Grabowski, 2018). Therefore, riverbank was retained as a potential source, but the high confidence intervals should be kept in consideration.

Variation in suspended sediment sources

(i) Inter-event variation

Inter-event variation in SS transport is often observed (Alexandrov et al., 2007; Gao et al., 2013; Sherriff et al., 2016). It is expected that this inter-event variation in total SSC is also expressed in varying SS sources (Legout et al., 2013). Therefore, SS source contributions and hydro-meteorological variables were compared at the inter-event scale. The event-based variables included total and source-specific SSCs (SSCt, SSCL, SSCM, SSCR, SSCC, and SSCU), together with discharge (Q) and antecedent precipitation totals (as a proxy variable for antecedent soil moisture conditions) for 1 day, 7 days and 21 days prior to the event (P1d, P7d, P21d) (e.g. Seeger et al., 2004; Perks et al., 2015).

(ii) Intra-event variation

To gain insights into the intra-event variation in SS sources, hysteresis patterns between discharge and (source-specific) SSCs were visually examined to investigate possible changes in the dominant SS source throughout individual events, and to assess the consistency of source-specific hysteresis patterns (i.e. to assess whether source-specific SSCs vary simultaneously throughout events).

Hydro-meteorological drivers

A multivariate analysis was performed to investigate the correlation between total SSC and source-specific SSCs with a range of hydro-meteorological variables in order to gain insights into drivers and processes controlling temporal variation in SS sources and how these variations relate to variations in the total SSC. The multivariate dataset included all sampled SSCs, estimated source-specific SSCs, discharge and precipitation at the time of sampling (Q and P1d, as well as well as Q1d, Q7d, Q21d) and precipitation (P1d, P7d, P21d) for the three monitoring stations (MT, PH and TR) (Figure 1).

Two types of multivariate analyses were done, each aimed at investigating a different level of correlation between the variables. First, a Pearson correlation analysis was performed to investigate pairwise correlations between SSC, source specific SSCs, and hydro-meteorological variables. Second, relationships were established between SSC and source-specific SSCs (X), and hydro-meteorological variables (X) to investigate whether SSC could be predicted based on these explanatory variables. To avoid selection of variables based on collinearity, PLSR was used. Compared to multiple linear regression, PLSR is better able to handle data with collinear and numerous explanatory variables (Martens and Martens, 2000; Karaman et al., 2013). Essentially, PLSR works similarly to principal component analysis (PCA), as it reduces a dataset with many variables (X; 14) and numerous measurements (observations; 159) into a few components by maximizing the covariance between the X and Y datasets (Wold et al., 2001).

In total, six SSC–PLSR models (i.e. one for the total SSC and five for the source-specific SSCs) were developed analogous to the approach described by Poulenard et al. (2009). The sum of squared PLSR loadings (SSL) were used as a measure to evaluate which hydro-meteorological variables define the model components (Martens and Martens, 2000; Wold et al., 2001; Karaman et al., 2013).

Results

Dominant suspended sediment sources

Limestone grassland was identified as the dominant SS source (average: 45% ± 12%), followed by urban street dust (average: 43% ± 10%) (Figure 2). Millstone and coals grassland contributed on average 19% (± 13%) and 14% (±10%) respectively, while eroding riverbanks accounted for 16% (± 18%) of the total SSC.

Variation in suspended sediment sources

(i) Inter-event variation

The varying relationship between SSC, discharge, and source contributions at the inter-event scale is illustrated in the time series of multiple discharge peaks in November 2016 and February 2017 (Figure 3). As discharge peaks in November 2016 progressed, limestone SSC (SSCL) appeared to decrease, while coals SSC (SSCC) slightly increased. Furthermore, urban street dust SSC (SSCU) appeared to be highest during the rising limb of the hydrographs, remaining an important source throughout the events, while riverbank SSC (SSCR) was slightly higher during the second half of the discharge peaks, despite the uncertainty associated with SSCR estimations (Figure 3a).
Figure 3. Discharge (Q) and sampled suspended sediment concentration (SSC) with estimated relative sediment source contributions (%) with associated confidence intervals (Table I) for sampled events in: (a) November 2016 and (b) February 2017. [Colour figure can be viewed at wileyonlinelibrary.com]

Figure 4. Hysteresis patterns between suspended sediment concentration (SSC) and discharge (Q) with estimated source-specific SSCs during high-flow events in (a) Jun-16(1), (b) Sep-16, (c) Nov-16(4), and (d) Feb-17(2). Sediment sources: grassland from the limestone (L), millstone grit (M), coals measures (C) areas, riverbanks (R), and urban street dust (U). Note that confidence intervals associated with the source-specific SSCs as shown in Table I should be considered. [Colour figure can be viewed at wileyonlinelibrary.com]
Similar trends in SSC$_L$ and SSC$_C$ were evident in discharge peaks in February 2017, while total SSC (SSC$_T$) appeared to decrease despite similar discharge peaks (Figure 4b).

While events in November 2016 were generally characterized by highest discharges and SCs, smaller events, in terms of discharge, were also observed with high SCs that were linked to different sources (Table II). For example, compared to other events, Jun-16 (1) was characterized by a low $Q_{\text{max}}$ ($31 \text{ m}^3 \text{s}^{-1}$) and $P_{\text{a}}$ (12 mm), but relatively high SCs ($107 \text{ mg l}^{-1}$) and a dominant contribution from urban street dust. Another example is the event Sep-16, which had an average $Q_{\text{max}}$ ($43.3 \text{ m}^3 \text{s}^{-1}$), but exceptionally high SCs ($1007.5 \text{ mg l}^{-1}$) with dominant contributions from eroding riverbanks.

(ii) Intra-event variation

At the intra-event scale, discharge-SC hysteresis patterns further illustrate the temporal variation in SS transport and sources (Figure 4). Most significantly, based on the samples taken, the source-specific SCs do not always follow the same hysteresis pattern (i.e. the source contributions are not constant or equally important throughout events).

In Jun-16(1), a tight counter-clockwise pattern was observed, with urban street dust as the dominant SS source (Figure 4a). Furthermore, the hysteresis patterns of SSC$_L$, SSC$_C$, SSC$_U$ and SSC$_C$ exhibited a consistent counter-clockwise pattern, while SSC$_R$ and SSC$_M$ were close to zero. Contrarily, the counter-clockwise hysteresis pattern in Sep-16 was characterized by slightly higher discharges and a very high SC peak (Figure 4b). At the start of the event, SSC$_C$, SSC$_L$, and SSC$_C$ increased consistently with SSC$_L$ and riverbank became the dominant SS source. However, SSC$_R$ decreased rapidly towards the end of the event, while SSC$_C$ decreased more gradually, which coincided with a slight increase of SSC$_C$. Furthermore, the Nov-16(4) event exhibited a clockwise-pattern whereby the dominant sediment source changed from urban street dust during the rise of the hydrograph, to coal grassland at peak discharges, and limestone grassland during the falling limb (Figure 4c). SSC$_C$, SSC$_C$, and SSC$_C$ hysteresis patterns were consistent with SSC$_L$, all showing a second SC peak during the falling limb of the hydrograph, while in SSC$_R$ a double peak was present before and after the second SC peak. Finally, Feb-17(2) was characterized by a complex hysteresis pattern with a counter-clockwise loop during the first peak, and a smaller clockwise during the second peak (Figure 4d).

The first peak was mainly characterized by SSC$_C$ (clockwise) and SSC$_R$ (counter-clockwise). During the second peak, SSC$_L$ and SSC$_C$ became dominant, both displaying a clockwise pattern.

### Hydro-meteorological drivers

The temporal analyses illustrated that total SCs, SS sources and hydro-meteorological variables vary substantially between and during high-flow events. In what follows, correlations and relationships between SCs and hydro-meteorological variables are further investigated to identify potential drivers for the observed temporal patterns.

(ii) Pairwise correlations

The Pearson correlation analysis confirmed significant correlations between SSC and hydro-meteorological variables (Table III). Correlations existed between total SCs and source-specific SCs: SSC$_L$ was positively correlated with SSC$_L$, SSC$_C$, while negatively correlated with SSC$_R$. Most discharge variables were also significantly correlated with precipitation variables, and strong correlations existed between precipitation variables at different monitoring stations. Furthermore, SCs were correlated to various hydro-meteorological variables (Table III). SSC$_L$ was correlated to discharge, $P_{\text{a}}$ and $P_{\text{d}}$ (mainly from PH). SSC$_C$ and SSC$_U$ were positively correlated with instantaneous precipitation, while negatively correlated with discharge and antecedent precipitation. A similar correlation was present for SSC$_C$, mostly with precipitation variables at MT. Contrarily, SSC$_M$ was positively correlated with antecedent discharge ($Q_{21\text{d}}$) and SSC$_C$ was positively correlated to antecedent precipitation at PH.

(ii) Predictive relationships

The results of the Pearson correlation analysis demonstrated covariation between many hydro-meteorological variables, which emphasizes the need to use statistical techniques such as PLSR which can handle high degrees of variable covariation. PLSR models were developed to estimate total and source-specific SCs as a function of hydro-meteorological variables (Table IV, Supporting Information). The SSC$_L$-PLSR model had the highest goodness-of-fit ($R^2 = 56.2\%$), while the root mean squared error of prediction (RMSEP) was highest for SSC$_C$-PLSR.

### Table II

| Number of SS samples | SSC$_{\text{mean}}$ | SSC$_{\text{max}}$ | SSC$_{\text{min}}$ | SSC$_{\text{a}}$ | SSC$_{\text{am}}$ | SSC$_{\text{ac}}$ | SSC$_{\text{d}}$ | Q$_{\text{mean}}$ | Q$_{\text{max}}$ | P$_{\text{a}}$ | P$_{\text{d}}$ | P$_{21\text{d}}$ |
|----------------------|---------------------|---------------------|---------------------|------------------|------------------|------------------|------------------|----------------|--------------|--------------|--------------|--------------|
| Aug-15               | 12                  | 92.9                | 90.6                | 7.0              | 24.7             | 2.5              | 2.9              | 13.3           | 11.9         | 21.5         | 74.1         | 13.1         | 28.2         | 69.3         |
| Nov-15               | 16                  | 33.9                | 46.7                | 14.7             | 16.8             | 0.0              | 1.6              | 14.1           | 6.1          | 72.3         | 72.0         | 122.0        | 5.3          | 16.0         | 158.6        |
| Mar-16               | 6                   | 19.8                | 27.4                | 12.5             | 12.4             | 4.3              | 0.0              | 15.5           | 0.0          | 26.7         | 40.9         | 0.5          | 53.8         | 81.9         |
| Jun-16(1)            | 10                  | 28.2                | 107.3               | 8.7              | 21.1             | 0.0              | 13.5             | 31.8           | 0.0          | 9.4          | 31.1         | 7.2          | 11.9         | 44.2         |
| Jun-16(2)            | 6                   | 47.1                | 103.4               | 8.3              | 19.2             | 0.0              | 33.5             | 31.9           | 0.0          | 16.5         | 30.7         | 10.6         | 33.6         | 49.2         |
| Aug-16               | 6                   | 15.9                | 18.7                | 13.0             | 7.7              | 2.3              | 0.0              | 7.0            | 4.9          | 13.5         | 23.2         | 15.0         | 54.2         | 81.4         |
| Sep-16               | 23                  | 179.4               | 1007.5              | 7.4              | 39.4             | 7.3              | 66.0             | 15.1           | 115.8        | 18.8         | 43.3         | 14.2         | 20.1         | 64.8         |
| Nov-16(1)            | 15                  | 42.8                | 151.0               | 3.3              | 31.6             | 20.9             | 1.9              | 17.9           | 2.1          | 18.2         | 37.6         | 2.7          | 8.4          | 22.2         |
| Nov-16(2)            | 8                   | 51.7                | 116.0               | 11.7             | 24.4             | 13.4             | 3.8              | 15.7           | 3.9          | 28.4         | 104.0        | 5.3          | 27.4         | 34.0         |
| Nov-16(3)            | 16                  | 37.6                | 97.8                | 12.3             | 18.1             | 3.3              | 5.6              | 15.9           | 0.7          | 47.0         | 72.0         | 4.8          | 44.7         | 57.7         |
| Nov-16(4)            | 13                  | 65.6                | 152.0               | 11.2             | 20.9             | 7.0              | 18.7             | 22.5           | 7.4          | 48.4         | 101.0        | 3.1          | 47.3         | 88.7         |
| Jan-17               | 6                   | 12.0                | 21.6                | 3.7              | 5.3              | 3.6              | 0.0              | 3.7            | 4.8          | 18.5         | 29.5         | 0.6          | 15.8         | 37.8         |
| Feb-17(1)            | 14                  | 98.3                | 243.5               | 36               | 34.2             | 33.3             | 14.9             | 46.3           | 1.7          | 37.8         | 88.2         | 6.2          | 12.8         | 50.4         |
| Feb-17(2)            | 8                   | 33.0                | 64.8                | 15.9             | 8.6              | 3.8              | 7.1              | 9.4            | 5.1          | 34.4         | 54.5         | 6.6          | 35.6         | 61.3         |

*Note that confidence intervals associated with the source-specific SCs as shown in Table I should be considered.*
Table III. Pearson correlation analysis between suspended sediment concentration (SSC), source-specific SSCs and hydro-meteorological variables (Q: discharge, P: precipitation, 1, 7 and 21 days antecedent Q and P).

|       | SSC  | SSC_L | SSC_M | SSC_U | SSC_R | Q_1d | Q_7d | Q_21d | P_1d | P_3d | P_7d | P_21d | PH_1d | PH_3d | PH_7d | PH_21d | PAT_1d | PAT_7d | PAT_21d | PAT_3d | PAT_4d |
|-------|------|-------|-------|-------|-------|------|------|-------|------|------|------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| SSC   | 1.00 |       |       |       |       |      |      |       |      |      |      |       |       |       |       |       |       |       |       |
| SSC_L | -0.36| 1.00  |       |       |       |      |      |       |      |      |      |       |       |       |       |       |       |       |       |
| SSC_M | -0.09| 0.10  | 1.00  |       |       |      |      |       |      |      |      |       |       |       |       |       |       |       |       |
| SSC_C | 0.24 | -0.16 | -0.46 | 1.00  |       |      |      |       |      |      |      |       |       |       |       |       |       |       |       |
| SSC_R | -0.32| 0.52  |       | 0.06  | 0.07  | 1.00 |      |       |      |      |      |       |       |       |       |       |       |       |       |
| Q_1d  | 0.41 | -0.52 | -0.22 | 0.00  | -0.51 |      |      |       |      |      |      |       |       |       |       |       |       |       |       |
| Q_7d  | 0.19 | -0.23 | -0.10 | -0.07 | -0.30 | -0.09 | 1.00 |      |      |      |      |       |       |       |       |       |       |       |       |
| Q_21d | 0.17 | -0.22 | -0.21 | -0.21 | -0.02 | 0.59 | 1.00 |      |      |      |      |       |       |       |       |       |       |       |       |
| P_1d  | -0.11| 0.06  | -0.16 | -0.21 | 0.00  | 0.00  | 0.62 | 0.73  | 1.00 |      |      |       |       |       |       |       |       |       |       |
| P_3d  | 0.07 | 0.07  | 0.24  | -0.25 | 0.09  | 0.01  | -0.16| -0.02 | 0.06 | 1.00 |      |       |       |       |       |       |       |       |       |
| P_7d  | 0.25 | -0.28 | 0.11  | -0.33 | 0.31  | -0.14| -0.23 | -0.34 | -0.19 | 0.11 | 0.09 | 0.10  | 0.00  | 0.00  | 0.08  | 0.46  | 1.00  | 0.00  | 1.00  |
| P_21d | 0.14 | -0.02 | -0.11 | -0.16 | -0.42 | -0.42 | 0.28 | 0.11  | 0.04 | 0.04 | 0.01 | -0.19 | 0.10  | 0.08  | 0.17 | 0.23  | 0.06  | 0.32  | 0.73  | 1.00  |
| PAT_1d| -0.10| 0.24  | 0.08  | -0.15 | 0.18  | -0.22 | 0.14 | 0.27  | 0.39 | 0.07 | 0.21 | 0.20  | 0.20  | 0.26  | 0.57  | 0.05  | 0.19  | 0.08  | 1.00  |
| PAT_7d| 0.45 | -0.12 | 0.13  | 0.18  | -0.14 | -0.11 | 0.51 | 0.00  | -0.21 | 0.05 | 0.74 | 0.20  | 0.06  | 0.04  | 0.66  | 0.12  | 0.11  | 0.03  | 1.00  |
| PAT_21d| -0.04| 0.25  | -0.03 | -0.32 | -0.42 | 0.04  | 0.60 | 0.45  | 0.22 | -0.18 | 0.14 | 0.06  | 0.52  | 0.29  | -0.05 | -0.03 | 0.19  | 0.41  | 0.09  | 0.19  | 1.00  |
| PAT_3d| 0.00 | -0.07 | -0.22 | -0.29 | -0.28 | 0.22  | 0.64 | 0.66  | 0.81 | -0.05 | -0.06 | 0.10  | 0.63  | 0.91  | -0.05 | 0.03  | 0.06  | 0.38  | 0.23  | 0.11  | 0.52  |

*Note that confidence intervals associated with the source-specific SSCs as shown in Table I were not taken into account in this analysis.

Bold numbers are significant at the 95% confidence level. L: limestone, M: millstone grit, C: coal, R: riverbank, U: urban street dust, MT: Malham Tarn, TR: Thornton Reservoir, PH: Proctor Heights.
Total suspended sediment concentration

Total SSC in the River Aire varied considerably during and between different rainfall events. High-flow events of similar (56.6 mg l$^{-1}$), which is partly attributed to the exceptionally high total SSCs during the event in September 2016. Generally, the models consisted of four to six components with a varying explained variance between 42% and 57%. In all models, the first component explained significantly more variance than the second component.

The loadings associated to the PLSR models were further examined to identify which hydro-meteorological variables define the model components (Figure 5). The SSC$_t$ and SSC$_L$ models were defined by a similar set of variables, with the first component determined by $P_{1d}$ and $Q$ (instantaneous precipitation and discharge), and the second component by $P_{21d}$, $P_{7d}$, $Q_{1d}$ and $Q_{7d}$ (antecedent precipitation and discharge).

The other source-specific SSCs appeared to be best predicted by a different combination of variables, suggesting the presence of different driving factors. In general, in the SSC$_M$, SSC$_C$, and SSC$_U$ models, precipitation variables at MT and TR were most important. Furthermore, both the SSC$_M$ and SSC$_C$ models were defined by the inverse of the SSC$_L$ model, with the first component determined by $P_{7d}$ and $P_{21d}$ and $Q_{7d}$ (antecedent precipitation and discharge), and the second component by $Q$ and $P_{1d}$ (instantaneous precipitation and discharge). The SSC$_U$ model was determined by $P_{1d}$ in the first component, and $Q$ in the second component (both instantaneous). Contrarily, the SSC$_R$ model was mainly determined by precipitation at PH (first component), while a wide range of variables defined the second component.

Discussion

This study combined high frequency monitoring of SSC during high-flow events with DRIFTS-based sediment fingerprinting to investigate the influence of SS source contributions and hydro-meteorological variables on temporal variations in SSC. Considerable temporal variability in SSCs and sources was observed during the monitored high-flow events, which can be linked to different hydro-meteorological variables and sediment transport process interactions.

Table IV. Model statistics of partial least squares regression (PLSR) between suspended sediment concentrations (SSCs) ($Y$) (total and source-specific) and hydro-meteorological variables ($X$) (RMSEP: root mean squared error of prediction).

| SSC  | SSC$_L$ | SSC$_M$ | SSC$_C$ | SSC$_R$ |
|------|---------|---------|---------|---------|
| $R^2$ (%) | 36.4 | 56.2 | 29.7 | 48.5 | 28.7 | 32.3 |
| RMSEP (mg l$^{-1}$) | 56.6 | 10.7 | 10.4 | 27 | 12.8 | 42.8 |
| Explained variance first component (%) | 32.57 | 41.51 | 26.98 | 20.99 | 33.09 | 15.13 |
| Explained variance second component (%) | 5.07 | 6.33 | 8.95 | 8.69 | 2.91 | 3.92 |
| Explained variance all components (%) | 56.2 | 57.53 | 41.88 | 48.51 | 49.93 | 31.08 |

*Note that confidence intervals associated with the source-specific SSCs as shown in Table I were not taken into account in this analysis.*
discharge exhibited differing peak SSCs and strong intra-event variation (Figure 3). Significant correlation was found between total SSC and instantaneous precipitation and discharge (Table III), which was also expressed in the PLSR components (Figure 5), suggesting the presence of a fast-response SS transport system (Bracken et al., 2015). Nevertheless, the predictive power of the PLSR model to estimate SSCs based on the chosen hydro-meteorological variables was generally low ($R^2$ of 36.4%), which indicates the difficulty in capturing variations in SSCs over time and could partially be explained by source-specific process interactions controlling total SSCs.

Suspended sediment sources and drivers

This study is one of the first of its kind to combine sediment fingerprinting at the event-scale with an analysis of the temporal variation in SSCs and hydro-meteorological variables in order to identify source-specific factors and process interactions controlling total SSC. This type of analysis is made possible thanks to the recent development of a time- and cost-efficient sediment fingerprinting approach (Poulenard et al., 2012), and the availability of detailed hydro-meteorological data within the catchment. However, the predictive power of the PLSR models to estimate source-specific SSCs is generally low, with the models for SSC_L and SSC_C performing better compared to SSC_t, while the other sources perform equally poor (Table IV). Therefore, any interpretation of the results needs to be done with consideration of these uncertainties. A more in-depth discussion on methodological considerations for future research is presented in the next section.

(i) Sediment from urban areas
High contributions from urban street dust were observed, reflecting the urban location of the point of sampling, which is in agreement with other studies within the Aire catchment that observed a significant impact from the urban environment on SSCs (Carter et al., 2003; Old et al., 2006) and SS-associated contaminants (Walling et al., 2003a).

Furthermore, the average street dust contribution during individual events was most strongly correlated to instantaneous discharge and precipitation (Figure 5). These results suggest that street dust contribution responds fast to precipitation and varies relatively constant with the total SSC (Figures 3 and 4), which demonstrates the proximity of urban area to the sampling location and the high degree of connectivity of the urban area to the river system (i.e. stormwater drainage system) (Figure 6).

(ii) Sediment from grassland areas
Even though grassland is generally considered to be less prone to soil erosion compared to arable land (i.e. presence of protective vegetation cover), considerable contributions of sediment from grassland areas to the SS were found in the River Aire. These high contributions could be the result of cattle grazing in the catchment (i.e. trampling causing detachment and mobilization of sediment particles or causing flow paths) (Trimble and Mendel, 1995; James and Alexander, 1998; Meyles et al., 2006; Bilotta et al., 2007; Peukert et al., 2014). Nevertheless, not all grassland areas were equally important in contributing to the SS, which appears to be controlled by the combination of antecedent precipitation and sediment connectivity (i.e. the capacity of the catchment to effectively transfer material towards the river determined by the presence/absence of physical blockages such as hills, ditches or plains) (Fryirs, 2013). In this study, urban areas are considered as main blockages preventing sediment from grassland areas to be transferred to the river system by obstructing (natural) flow paths as a result of e.g. build-up areas, parks and gardens, ditches and road verges (Figure 6).

Sediment from limestone grassland (SSC_L) was most strongly correlated to total SSC and showed a similar correlation to event-based hydro-meteorological variables ($P_{1d}$ and $Q_t$). This corresponds with the observation that limestone grassland was the dominant sediment source in the River Aire during the monitored period (Figure 2) and that limestone grassland contribution remained significant throughout events (e.g. Figure 4). However, the limestone area is also the most distant source area from the point of sampling (40–45 km). These findings could indicate that a ready-available supply of limestone grassland sediment is available within the river system (e.g. stored on the river

Figure 6. Conceptual illustration of the suspended sediment transport dynamics and connectivity in the River Aire catchment. [Colour figure can be viewed at wileyonlinelibrary.com]
bed (Poulenard et al., 2012; Shennif et al., 2016). The presence of a high limestone-sediment supply could possibly be explained by higher erosion rates in the upper part of the catchment due to the steeper topography and higher connectivity of the landscape to the river (i.e., predominantly grassland with few urbanized areas) compared to the other grassland areas (Fryirs, 2013) (Figure 6). This hypothesis is supported by the observation that sediment contribution from PH (located in a steep part of the catchment; Figure 1) was especially correlated to the SSC.

Contrarily, SSCs from the millstone and coals grassland were mainly correlated to antecedent precipitation and discharge. The middle and lower parts of the catchment are characterized by more gentle slopes, and the grassland areas are often not directly connected to the river system due to a higher degree of urbanization (Figures 1 and 6). Especially the coals grassland area is very scattered within predominant urban area and is not well connected to the river system. This hypothesis would imply that more prolonged precipitation (i.e., antecedent precipitation) is required to connect (or transfer) the eroded material to the river system (Fryirs, 2013), and could also explain the lag-time in the coals grassland contribution during events (Figure 3 and 4).

(iii) Sediment from eroding riverbanks
Riverbank material was not found to be a dominant source of SSC at the point of sampling and was the least well correlated to hydro-meteorological variables. Part of this lack of correlation is likely linked to the low degree of discrimination of riverbank material from other source material and the associated high uncertainty on the estimated contributions.

Nevertheless, the lack of correlation with hydro-meteorological variables could also be explained by the episodic, less predictable, nature of riverbank erosion such as riverbank collapse, which would result in a sudden contribution as observed for the event in Sep-16 (Figure 4b). Yet, the sampling frequency might not have been sufficient to have captured other sudden collapses of highly localized river banks. Furthermore, despite the high uncertainty, slight increases in riverbank contributions appear to be present towards the second-half of events (i.e., lag-time between the location in the River Aire, indicating the location and erosion dynamics of these source areas (i.e., fast mobilization to and within river). Contrarily, contributions from millstone and coals

Methodological considerations
As discussed in the methodology, the sediment fingerprinting method used in this study presents tremendous opportunities to investigate variations in SS sources at a fine temporal resolution because it is more time and cost efficient than traditional sediment fingerprinting methods (Poulenard et al., 2009). However, there are some methodological considerations to consider when interpreting the results.

First, the design of the sediment fingerprinting method used in this study (i.e., individual, source-specific PLSR models using DRIFTS) strongly differs from traditional sediment fingerprinting methods (i.e., based on a mass balance equation using geochemistry or fallout radionuclides) (Pulley and Collins, 2018). Because of these differences in design, standard techniques to assess the impact of particle size variations, source groupings, and tracer conservatism (Laceby et al., 2017) are not directly transferable to the DRIFTS–PLSR method. Due to the experimental and explorative design of the study, these aspects, as well as error propagation across different analyses, were not investigated further but remain important steps to produce reliable results (Vercruysse and Grabowski, 2018). Towards future development and use of sediment fingerprinting to investigate sediment transport processes, further methodological testing with regards to particle size and conservatism will be required (Vercruysse and Grabowski, 2018), as well as exploring possibilities of combining different sediment fingerprinting methods. Especially in the case for riverbank material, combination with other methods is advisable, for example using DRIFTS with X-ray fluorescence spectroscopy and geochemistry (Cooper et al., 2014, 2015).

Furthermore, comparison of results in this study with a previous sediment fingerprinting study in the Aire catchment (Carter et al., 2003), indicates two other critical methodological aspects that need to be considered. First, Carter et al. (2003) used submersible pumps to collect 70 SS samples between November 1997 and January 1999 (mostly) during high-flow events. Contrarily, this study is based on a more extensive dataset of 159 SS samples taken during 14 high-flow events between June 2015 and March 2017 with a depth-integrating sampler. While still based on discrete manual samples, the sampling design of this study allowed the investigation of variations in SS sources at a much finer temporal resolution, which enabled the identification of significant variation depending on the time of sampling. Second, while in this study all SS samples were taken at a single location within Leeds city centre (reflected in the high urban contribution to SS), Carter et al. (2003) took SS samples at five locations upstream of the city centre (Figure 6). Due to their spatially distributed study design, it was demonstrated that dominant SS sources vary considerable along the profile of the river.

In short, interpretation of SS source information in terms of drivers for SS transport will be influenced by the timing, frequency, and location of SS sampling. To capture the full spatio-temporal variation in SS transport, it is essential to take SS samples during different high-flow events throughout the year and in succession, while also adopting a spatially distributed sampling campaign (Perks et al., 2017).

Conclusion
This study demonstrated the potential and importance of combining sediment fingerprinting with statistical analysis of hydro-meteorological data to investigate temporal variation in SSCs in rivers in terms of varying source contributions and hydro-meteorological variables and to gain better understanding of sediment connectivity at the catchment scale.

In general, contributions from street dust and limestone grassland follow similar patterns as the total SSC at the sampled location in the River Aire, indicating the location and erosion dynamics of these source areas (i.e., fast mobilization to and within river). Contrarily, contributions from millstone and coals

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grassland are less consistent, and driven by antecedent hydro-
meteorological conditions (i.e. lag-time between soil erosion and
sediment delivery to river). Riverbank material was poorly
correlated to hydro-meteorological factors. While this lack of
correlation is likely linked to the low degree of discrimination of
riverbank material from other source material, it could also
be linked to the more episodic nature of riverbank erosion
(i.e. bank collapse).

These differences in source-specific drivers and processes for
sediment transport demonstrate the difficulty in generalizing sediment transport patterns. The presented
methodology and associated interpretation of results creates
opportunities towards evaluating temporal variation in SSCs
from a catchment perspective. Further advancement of the
approach, including identification of different sources of
uncertainty associated with the DRIFTS-based method and
subsequent multivariate analysis, will help the development
of source-specific erosion and sediment transport models and
inform targeted soil and water conservation plans, both in terms
of quantity (i.e. when is SSC too high) and quality (i.e. where
does SS come from).

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10.17862/cranfield.rd.5903923).

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Supporting Information

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

**Table SI.** PLSR observed-predicted plots for the sediment fingerprinting models

**Table SII.** PLSR plots for the SSC predictive models based on hydro-meteorological variables