

A regime-based framework for linking runoff initiation and event-scale sediment export in a small temperate agricultural loess catchment

Pierre Baert^{a,*}, Matthieu Herpoel^a, Jeroen Meersmans^a, Charles Bielders^b, Aurore Degré^a

^a TERRA Teaching and Research Centre, Gembloux Agro-Bio Tech, University of Liège, 5030 Gembloux, Belgium

^b Earth and Life Institute, Université Catholique de Louvain, 1348 Louvain-la-Neuve, Belgium

ARTICLE INFO

Keywords:

Runoff initiation
Initial abstraction ratio
SCS-CN
MUSLE
Sediment export
Agricultural catchment
Loess soils

ABSTRACT

Runoff initiation is a major uncertainty in event-scale erosion modelling, particularly in small agricultural catchments where sediment export is controlled by threshold-like hydrological responses. This study developed a regime-based framework to analyse how alternative representations of runoff initiation affect runoff volume, peak discharge, and sediment-yield prediction in a small temperate agricultural loess catchment in Wallonia, Belgium. The analysis included 154 rainfall–runoff events monitored between 2015 and 2023, of which 46 had complete suspended-sediment observations. Runoff initiation was represented by the initial abstraction ratio λ of the Soil Conservation Service Curve Number model. Event-specific optimised λ values were derived from observed rainfall–runoff responses and generalised using K-means regimes and continuous regression based on hydro-meteorological descriptors. These formulations were used to estimate runoff volume and peak discharge, which were then supplied as inputs to the Modified Universal Soil Loss Equation. Fixed and literature-based λ formulations performed poorly, with a best runoff-volume Nash–Sutcliffe efficiency (NSE) of 0.13. Five regimes provided a strong diagnostic summary, preserving runoff volume (NSE = 0.94) and peak discharge (NSE = 0.67). Under out-of-sample prediction, regime performance declined to NSE = 0.21 for runoff volume and –0.26 for peak discharge, whereas the continuous formulation achieved NSE = 0.40 and 0.34, respectively. Predictive sediment-yield performance remained poor for both approaches (NSE = –0.03 and 0.01). The framework distinguishes diagnostic structure from predictive performance and clarifies how hydrological uncertainty affects event-scale sediment-export modelling.

1. Introduction

Runoff generation in agricultural catchments results from nonlinear interactions between rainfall forcing, antecedent wetness, soil surface condition, land management, and hydrological connectivity. Hydrological connectivity refers here to the event-dependent activation and connection of runoff pathways that allow water and sediment to move from cultivated hillslopes towards the catchment outlet (Bracken and Croke, 2007; Bracken et al., 2015). These interactions determine not only whether runoff is initiated, but also how efficiently rainfall is converted into overland flow, peak discharge, and sediment export (Mirus and Loague, 2013). Consequently, relatively small differences in runoff initiation may produce large contrasts in sediment delivery, particularly where surface sealing, crusting, roughness, crop cover, and field-scale connectivity vary rapidly over time (Evrard et al., 2010; Hrachowitz et al., 2013; Boardman et al., 2019).

This issue is particularly relevant in the low-relief agricultural loess landscapes of northwestern Europe. These areas are characterized by humid temperate climates, deep and highly erodible silt-loam soils, intensive cropping systems, strong seasonal variations in vegetation cover and soil surface state, and runoff pathways that are often ephemeral rather than permanent (Evrard et al., 2010; de Vente et al., 2013; Datry et al., 2014). Under such conditions, event-scale erosion cannot be explained by rainfall magnitude alone. Moderate rainfall may generate substantial runoff and sediment export when it occurs under wet antecedent conditions, limited crop protection, surface crusting, or high hydrological connectivity (Evrard et al., 2010). Conversely, more intense rainfall may produce a limited response when storage and infiltration capacities remain high. Understanding sediment export therefore requires consideration of the threshold conditions that control runoff initiation and the subsequent connection of sediment sources to the catchment outlet (Poesen et al., 2003; Evrard et al., 2010; Boardman

* Corresponding author.

E-mail address: pierre.baert@uliege.be (P. Baert).

<https://doi.org/10.1016/j.catena.2026.110497>

Received 2 June 2026; Received in revised form 27 July 2026; Accepted 5 August 2026

Available online 18 August 2026

0341-8162/© 2026 Elsevier B.V. All rights are reserved, including those for text and data mining, AI training, and similar technologies.

et al., 2019; Owens, 2020).

Despite the episodic nature of these processes, erosion assessment in European agricultural landscapes still frequently relies on annual or long-term approaches, including frameworks derived from the Revised Universal Soil Loss Equation (RUSLE; Renard et al., 1997). Such approaches provide useful estimates of average soil loss but do not explicitly represent individual runoff events, the activation of hydrological connectivity, or the disproportionate contribution of a limited number of events to annual sediment export (Panagos et al., 2015; Alewell et al., 2019). Event-based approaches are therefore needed to investigate how runoff initiation influences runoff volume, peak discharge, and sediment yield. The Modified Universal Soil Loss Equation (MUSLE) is useful in this context because it replaces rainfall erosivity with a runoff-energy term combining runoff volume and peak discharge (Williams, 1972, 1975). However, because event sediment yield in MUSLE is directly driven by runoff volume and peak discharge, uncertainties in these hydrological inputs impact the resulting sediment-yield estimates (Odongo et al., 2013).

A widely used empirical method for event runoff estimation is the Soil Conservation Service Curve Number method (SCS-CN; USDA-NRCS, 2021). Within this framework, runoff initiation is represented through the initial abstraction term, which aggregates interception, depression storage, and infiltration losses occurring before runoff is initiated. Initial abstraction is commonly expressed as a fixed fraction of potential maximum retention through the initial abstraction ratio λ . The classical value $\lambda = 0.20$ has long been questioned because it may delay simulated runoff initiation and underestimate runoff from small to moderate rainfall events. Lower values, particularly $\lambda = 0.05$, have consequently been proposed (Soil Conservation Service (SCS), 1972; Aron et al., 1977; Woodward et al., 2003; Hawkins et al., 2008). However, studies conducted under contrasting environmental conditions have shown that no single fixed ratio adequately represents event-scale runoff initiation across different climates, soils, land uses, and catchment states (Baltas et al., 2007; Fu et al., 2011; Caletka et al., 2020).

The structural validity of a fixed λ is especially questionable in cultivated catchments, where antecedent wetness, soil surface properties, crop development, and connectivity may change markedly between events (Michel et al., 2005; Hawkins and Woodward, 2019). Modified SCS-CN formulations have therefore allowed runoff initiation to vary with antecedent moisture, storm duration, rainfall characteristics, or storage-related indicators (Jain et al., 2006; Mishra et al., 2006). These approaches implicitly shift the interpretation of λ from a universal coefficient towards an effective event-dependent descriptor of catchment response. In the present study, SCS-CN is accordingly used as a parsimonious empirical structure for diagnosing runoff-initiation variability rather than as a complete process-based representation of runoff generation. MUSLE is similarly used as a runoff-driven modelling testbed through which the consequences of alternative runoff-initiation representations can be evaluated.

Previous studies have demonstrated that the SCS-CN initial abstraction ratio and Curve Number (CN) often require local or event-dependent adjustment to improve runoff estimation (Caletka et al., 2020). Other studies have coupled SCS-CN-type runoff estimates with erosion or sediment-yield models to represent the effect of hydrological response on event soil loss and sediment export (Gao et al., 2012). Nevertheless, three gaps remain. First, event-scale runoff, peak-discharge, and sediment measurements remain scarce in temperate agricultural loess catchments without permanent streamflow, largely because their intermittent and short-lived hydrological response is difficult to monitor. Second, although the variability of initial abstraction is widely recognized, it remains unclear whether event-scale runoff initiation is more usefully represented as a continuously varying parameter or as a limited number of recurrent effective response states. Third, it remains unclear how alternative representations of runoff initiation affect runoff volume and peak discharge estimates and, in turn, influence sediment-yield prediction.

Addressing these gaps may advance process understanding by revealing whether apparently heterogeneous rainfall-runoff responses contain a recurrent structure associated with distinct effective catchment states. Such states should not necessarily be interpreted as independent physical classes, because they may integrate several unresolved controls, including antecedent wetness, soil surface condition, crop stage, tillage, and hydrological connectivity. Nevertheless, identifying recurrent response states may provide a more interpretable representation of event behaviour than either a universal abstraction ratio or an unconstrained event-specific parameter.

The monitored catchment considered in this study combines several characteristics typical of intensively cultivated loess landscapes in northwestern Europe: low relief, highly erodible silt-loam soils, large cultivated fields, and an ephemeral drainage network. It therefore provides a relevant case study for examining how event-dependent runoff initiation influences hydrological connectivity and sediment export. Although the numerical parameter values and inferred response states remain site-specific, the processes investigated are relevant to a broader class of temperate agricultural catchments in which runoff pathways are activated intermittently.

The primary objective of this study is diagnostic and interpretive: to determine whether event-scale runoff initiation can be meaningfully summarized as a limited number of effective hydrological response states and to evaluate how these states affect runoff volume, peak discharge, and sediment export. A secondary objective is predictive: to assess whether runoff-initiation states can be inferred from available hydro-meteorological descriptors and to compare this regime-based representation with a continuous regression-based formulation. The novelty of the study lies not in the individual modelling or statistical methods, but in their combined use to distinguish diagnostic runoff-initiation structure from predictive regime assignment and to assess the consequences of runoff-initiation prediction errors for subsequent runoff and sediment predictions.

2. Materials and methods

2.1. Study site

The study was conducted in an 83.84-ha agricultural catchment located in Chastre, Wallonia, Belgium. The catchment outlet is located at 50°36'15.4" N and 4°35'19.0" E, within the silt-loam region of central Belgium and the northwestern European loess belt (Fig. 1A). Quaternary loess deposits have produced deep, fertile soils that are highly susceptible to runoff-driven erosion under intensive agricultural use. The landscape is dominated by open-field agriculture, with large cultivated parcels and few permanent semi-natural elements.

The catchment has no permanent stream. Surface water is conveyed through an ephemeral drainage network that becomes active during rainfall-runoff events. The main thalweg crosses cultivated fields and directs runoff towards the gauging station at the outlet. Catchment and field boundaries, the mapped drainage network, the meteorological station, outlet equipment, and hedges are shown on the 2022 ortho-photograph (Fig. 1B). Hedges occur along limited sections of the main thalweg but do not form a continuous vegetated buffer. Runoff-pathway activation and continuity may therefore vary among events according to rainfall forcing, soil-surface condition, and field management.

The regional climate is temperate oceanic according to the Köppen-Geiger classification (Cfb). Climatological normals for Chastre indicate a mean annual air temperature of approximately 10.3 °C and mean annual precipitation of about 820 mm for the 1991–2020 reference period (IRM-KMI, 2023). Elevation ranges from approximately 161 m along the upper catchment boundary to 138 m at the outlet. Slopes range from 0.2% to 17%, with a catchment mean of 3.8% (Fig. 2A).

Soils are dominated by Luvisols (74.3%) and Colluvic Regosols (21.7%), with smaller areas of Haplic Luvisols (2.5%) and Cambisols (1.5%) (Fig. 2B). Luvisols mainly occupy upper- and mid-slope

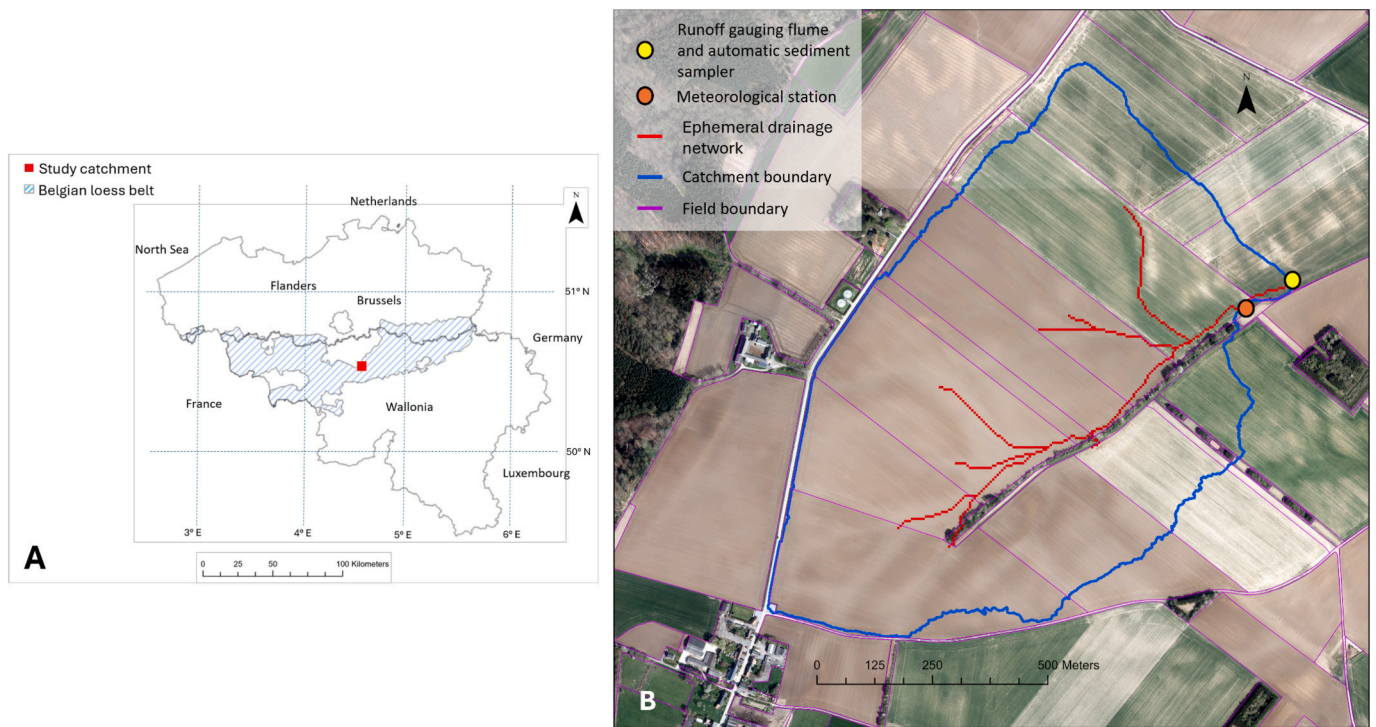


Fig. 1. Location and monitoring layout of the Chastre agricultural catchment. (A) Catchment location in Belgium and within the central Belgian loess belt. (B) 2022 orthophotograph showing catchment and field boundaries, the mapped ephemeral drainage network, the meteorological station, and the monitored outlet. The red symbol in Panel A indicates the catchment location. Source: Service Public de Wallonie. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

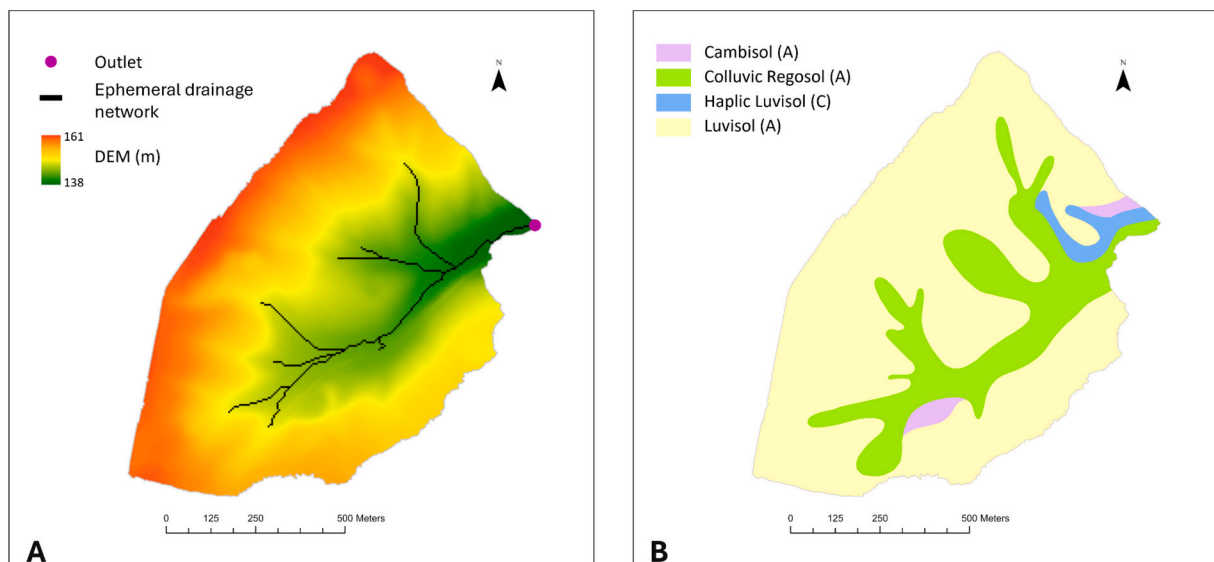


Fig. 2. Topographic and pedological characteristics of the study catchment. (A) Digital elevation model showing catchment elevation, the mapped ephemeral drainage network, and the monitored outlet. (B) Distribution of the main soil groups: Cambisols, Colluvic Regosols, Haplic Luvisols, and Luvisols. Letters in parentheses indicate the corresponding SCS-CN hydrologic soil groups. Source: Service Public de Wallonie and Demarcin et al. (2011).

positions, whereas Colluvic Regosols occur along drainage axes and reflect long-term sediment redistribution (Pineux et al., 2017). Land use is almost exclusively arable. Fields range from approximately 7 to 24 ha and are managed under conventional rotations including winter wheat, sugar beet, industrial chicory, maize, and potato. Permanent grasslands and vegetated buffer strips are absent, apart from discontinuous hedges near the main thalweg. These characteristics provide a relevant setting for investigating runoff initiation and sediment export in intensively

cultivated, low-relief loess landscapes with intermittently activated surface-flow pathways.

2.2. Monitoring setup and data acquisition

Rainfall, runoff, and suspended sediment were monitored between 2015 and 2023. Runoff and sediment were measured at the catchment outlet, whereas rainfall was recorded at an adjacent meteorological

station located at 50°36'15.4" N and 4°35'16.8" E (Fig. 1B).

Rainfall was measured at 1 min resolution with an OTT Pluvio² L weighing rain gauge. A Campbell Scientific ARG100 tipping-bucket gauge, with a resolution of 0.20 mm per tip, served as a control instrument and replaced the weighing-gauge record when a documented malfunction occurred. Rainfall data were aggregated to 5 min intervals.

Runoff was monitored with a stainless-steel San Dimas-type flume with a 0.30 m throat width. Water depth was measured by a pressure sensor connected to a Sigma 950 monitoring and logging system. Discharge was derived from a site-specific stage–discharge relationship and recorded at 5 min intervals.

Suspended sediment was collected with a 24-bottle automatic sampler activated when water depth in the flume exceeded 2.5 cm. Following Pineux et al. (2017), 500 mL samples were collected every 5 min for up to 120 min. Samples were dried and weighed, and suspended-sediment concentration was calculated from dry sediment mass and sampled water volume. Runoff data were supplied to the authors as laboratory-processed results derived from the original measurements and screened by the laboratory according to the observed data quality. Sediment data corresponded to the final laboratory results. The authors did not modify the original measurements and did not have access to the original field records, monitoring logbooks, or detailed laboratory quality-control procedures. Consequently, the analyses were performed using the processed dataset supplied by the laboratory. The available information on the monitoring equipment, rating relationship, sampling programme, and laboratory procedures is summarized in Supplementary Methods SM1.

2.3. Event selection and dataset construction

Rainfall events were separated using the inter-event definition proposed by Wischmeier (1959): successive events were considered independent when separated by at least 6 h during which cumulative rainfall remained below 1.27 mm. Events with total rainfall below 1.27 mm were not retained because none generated measurable runoff. The threshold was maintained because rainfall depths of this magnitude may produce runoff and erosion under temperate Belgian conditions when antecedent wetness is high or vegetation cover is limited (Laurant and Bollinne, 1976).

Between 2015 and 2023, 2766 rainfall events were delineated, of which 1057 exceeded 1.27 mm (Table 1). Among these, 169 generated measurable runoff and had sufficiently complete rainfall and discharge records for initial consideration. Fifteen events were excluded because their observed runoff depth exceeded the maximum runoff representable by the adopted SCS–CN parameterisation at $\lambda = 0$; consequently, no feasible non-negative value of λ could reproduce their observed response. The remaining 154 events constituted the hydrological dataset used to analyse runoff initiation, runoff volume, and peak discharge. The complete feasibility criterion and the inventory of excluded events are

provided in Supplementary Methods SM2. Of the 154 events, 46 also had complete and synchronized rainfall, discharge, and suspended-sediment observations and formed the sediment-yield subset. The annual distribution of both datasets was uneven, showing that the number of monitored responses was not proportional to annual rainfall depth alone.

Based on the processed dataset supplied by the laboratory, the remaining 108 runoff events could not be treated as zero-sediment events because sediment concentration was measured by event-triggered discrete sampling rather than continuously. Some events had incomplete sampling sequences, whereas others had no usable samples. The dataset available to the authors was therefore insufficient to distinguish an absence of sediment export from missing, incomplete, or laboratory-rejected observations.

For each hydrological event, rainfall depth and duration, runoff depth and volume, and peak discharge were derived from the monitored time series. Runoff volume was obtained by integrating the 5 min discharge series over the event hydrograph, and peak discharge was the maximum recorded discharge. For the 46 sediment events, concentrations were associated with the corresponding 5 min discharge intervals. Sediment flux was calculated from concentration and discharge, and observed event sediment yield was obtained by integration over the hydrograph. Equations, unit conversions, synchronization rules, and completeness criteria are provided in Supplementary Methods SM2.

Only events identified as having complete and usable sediment results in the laboratory-supplied dataset were included in the sediment subset. The original field records and detailed laboratory quality-control information were not available to the authors; therefore, the individual reasons for excluding the other events could not be reconstructed. The resulting 46-event subset may underrepresent high-rainfall or high-runoff conditions, and this limitation was considered when interpreting MUSLE performance.

Rainfall kinetic energy and maximum 30-min rainfall intensity (I_{30}) were calculated from the 5 min rainfall record. Unit rainfall kinetic energy was estimated using the bounded exponential intensity–energy relationship adopted in RUSLE2 (McGregor et al., 1995), consistent with the RUSLE framework used for regional erosion assessment in Wallonia. I_{30} was the highest mean intensity over any six consecutive 5 min intervals. Full equations are given in Supplementary Methods SM2. Fig. 3 shows the monthly distribution of rainfall depth and observed sediment yield for the 46 sediment events, and the complete inventory of the 154 rainfall–runoff events is provided in Table SM3.

2.4. Overview of the modelling workflow

Fig. 4 summarizes the modelling workflow. For every runoff-initiation formulation, the estimated initial abstraction ratio λ was introduced into the SCS–CN equation to calculate event runoff depth. Runoff depth was converted to runoff volume, and the resulting

Table 1

Annual rainfall and event counts at successive stages of dataset construction between 2015 and 2023. Rainfall values associated with each event category are cumulative annual totals. The final hydrological dataset comprised 154 rainfall–runoff events, including 46 events with complete and usable suspended-sediment results in the laboratory-supplied dataset. The total row reports event counts only.

	Annual rainfall (mm)	All rainfall events (#)	Events > 1.27 mm (#)	Rainfall in events > 1.27 mm (mm)	Rainfall-runoff events retained for hydrological modelling (#)	Rainfall associated with runoff events (mm)	Events with complete sediment observations (#)	Rainfall associated with events with complete sediment observations (mm)
2015	762	303	118	689	8	106	4	35
2016	837	334	130	748	20	180	3	26
2017	742	318	131	658	9	59	0	0
2018	604	301	95	514	4	67	2	56
2019	671	284	117	604	14	178	9	125
2020	638	309	118	565	8	80	3	29
2021	922	345	113	829	51	529	8	108
2022	583	243	92	515	18	212	8	108
2023	917	329	143	839	22	240	9	111
Total	–	2766	1057	–	154	–	46	–

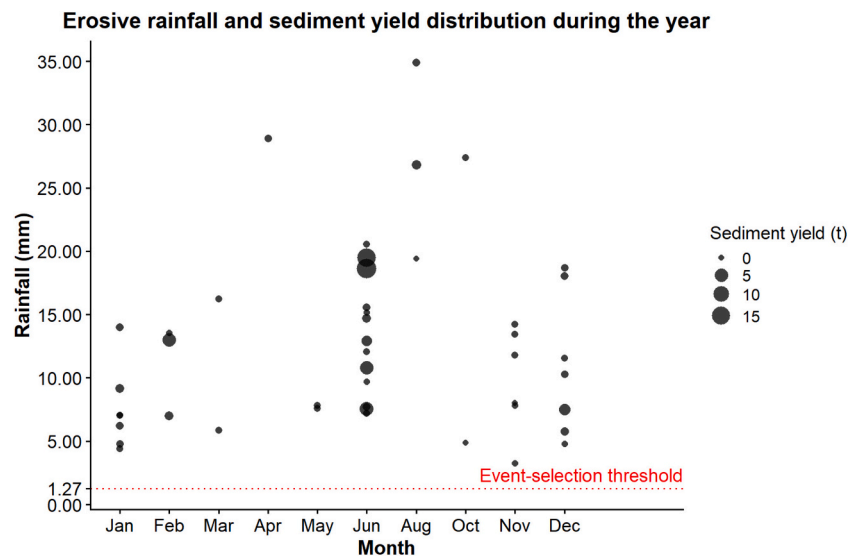


Fig. 3. Monthly distribution of event rainfall depth and observed sediment yield for the 46 rainfall–runoff events with complete and synchronized suspended-sediment observations between 2015 and 2023. Symbol size is proportional to observed event sediment yield (t), and the dashed line marks the 1.27 mm rainfall threshold used for event selection.

Hydrological and sediment yield modeling workflow

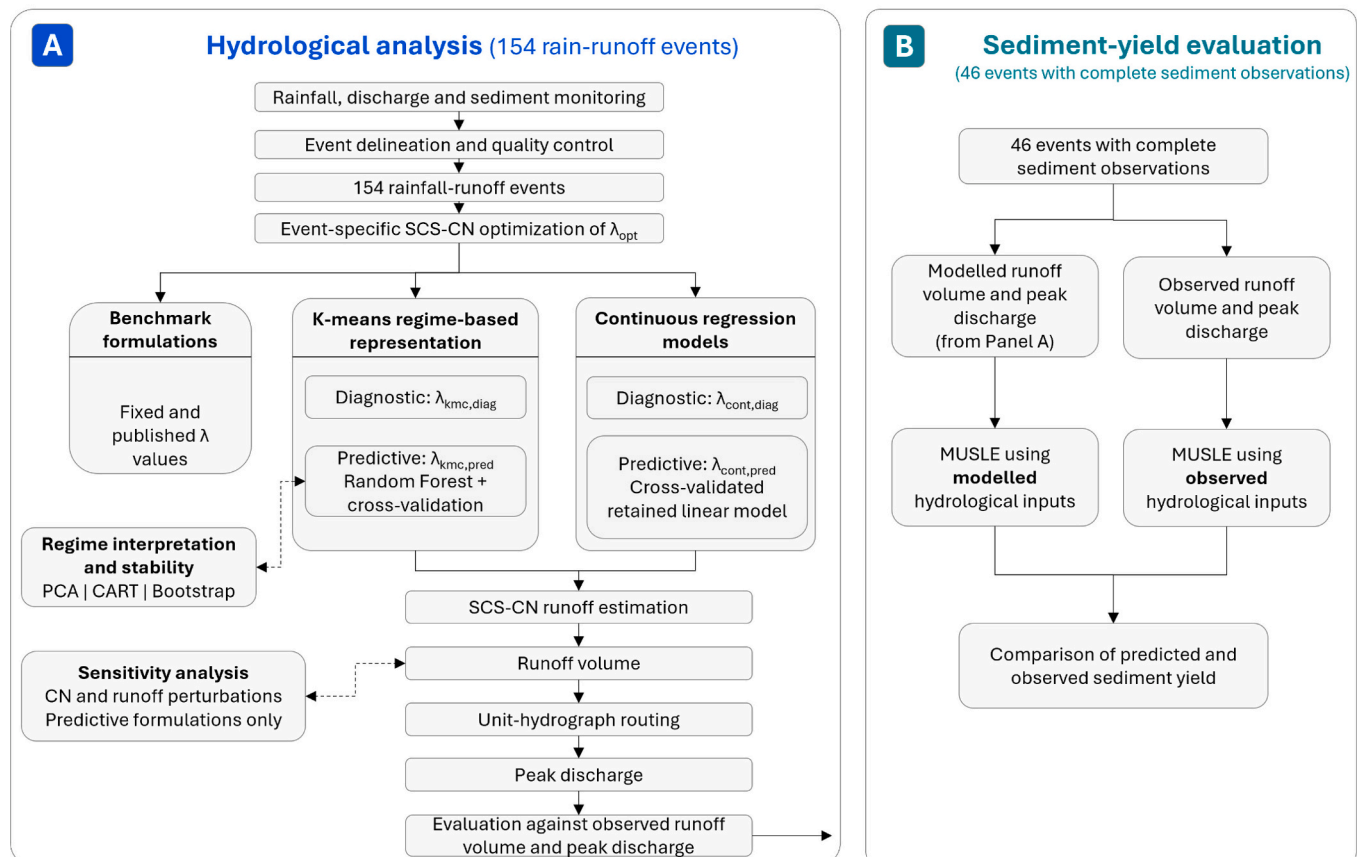


Fig. 4. Hydrological and sediment-yield modelling workflow. (A) Event-specific optimal initial abstraction ratios (λ_{opt}) were derived for 154 rainfall–runoff events and represented using fixed and published benchmarks, K-means regimes, or continuous regression. Diagnostic and cross-validated predictive formulations were used in the SCS-CN runoff calculation and unit-hydrograph routing procedure to estimate runoff volume and peak discharge. Principal component analysis, classification and regression tree analysis, bootstrap resampling, and sensitivity analyses supported regime interpretation and stability assessment. (B) For the 46 events with complete sediment observations, MUSLE predictions based on modelled or observed hydrological inputs were compared with observed sediment yield.

effective-rainfall series was routed using a common unit-hydrograph procedure to estimate peak discharge. For the 46 events with complete sediment observations, runoff volume and peak discharge were subsequently used as inputs to MUSLE. Annual Curve Number values, temporal resolution, and routing settings were identical across formulations, so differences in model outputs primarily reflected the representation of runoff initiation.

For each of the 154 retained rainfall–runoff events, an event-specific optimal initial abstraction ratio (λ_{opt}) was obtained by matching SCS–CN-simulated runoff to observed runoff. Because the response of the same event was used in this optimisation, λ_{opt} was interpreted as an event-derived indicator of effective runoff-initiation state, not as an independently predicted or directly measurable parameter.

Three groups of formulations were compared. Fixed λ values and published parameterisations were first evaluated as benchmarks. Second, λ_{opt} values were summarized by K-means regimes. In the diagnostic application, each event was assigned from its own λ_{opt} and represented by its regime centroid. In the predictive application, regime membership was inferred from hydro-meteorological descriptors using a Random Forest classifier (Breiman, 2001), fitted within cross-validation. Principal component analysis (PCA), classification and regression tree (CART) and bootstrap resampling were used only to interpret the retained regimes and assess their stability. Third, λ_{opt} was modelled as a continuous function of hydro-meteorological descriptors. Full-data fits were used for diagnostic reconstruction, whereas cross-validated fits were used for out-of-sample prediction.

The two predictive approaches were tested by perturbing Curve Number and observed runoff to assess the sensitivity of derived λ values and subsequent runoff volume estimates. MUSLE was then evaluated using modelled or observed hydrological inputs, separating hydrological effects from residual sediment–yield error.

2.5. SCS–CN parameterisation and event-specific optimisation of the initial abstraction ratio

The SCS–CN method was used as a controlled empirical framework for comparing runoff-initiation formulations rather than as a complete process-based representation of catchment response. Event runoff depth R (mm) was calculated as:

$$R = \frac{(PI_a)^2}{P - I_a + S} \quad \text{if } P > I_a \quad (1)$$

$$R = 0 \quad \text{if } P \leq I_a$$

where P is the rainfall depth (mm), I_a is the initial abstraction (mm), and S is the potential maximum retention (mm). Initial abstraction is defined as:

$$I_a = \lambda \cdot S \quad \text{with } S = \frac{25400}{CN} - 254 \quad (2)$$

where CN is the Curve Number.

Hydrologic soil groups were treated as static descriptors because they represent relatively persistent soil properties controlling infiltration and runoff potential (USDA–NRCS, 2004). Their spatial distribution was obtained from the Walloon map developed by Demarcin et al. (2011). Combined with annual land cover, they were used to assign CN values and calculate an area-weighted catchment CN for each year. In contrast, antecedent soil water content varies among events but was not represented using discrete antecedent-moisture CN classes. Combining these classes with an event-specific λ would introduce two concurrent adjustments for event-scale catchment conditions. Instead, λ was interpreted as an effective event-scale parameter reflecting variations in antecedent wetness and initial rainfall losses (Woodward et al., 2003).

For each retained rainfall–runoff event, λ_{opt} was estimated by

bounded numerical minimization of the squared difference between observed and SCS–CN-simulated runoff depth, with $\lambda \geq 0$ and $I_a < P$. Events for which observed runoff exceeded the maximum value representable at $\lambda = 0$ were excluded before optimisation. Full details of the feasibility criterion, parameter bounds, grid-search procedure, and treatment of boundary solutions are provided in Supplementary Methods SM2. It was subsequently used as the target for the regime-based and continuous generalisation approaches. Benchmark simulations used fixed ratios of $\lambda = 0.20, 0.05$, and 0.01 . The conventional value of 0.20 represents the original SCS–CN assumption (USDA–NRCS, 2021), whereas 0.05 has been recommended by reanalyses of event datasets (Woodward et al., 2003; Hawkins et al., 2008). The value 0.01 was included as a lower benchmark based on reported site-specific values of similar magnitude (Mishra and Singh, 2004; Baltas et al., 2007).

For the $\lambda = 0.05$ and 0.01 simulations, annual CN values derived under the conventional $\lambda = 0.20$ assumption were retained without recalibration. These configurations isolated the effect of changing λ and were not intended as jointly recalibrated CN – λ parameterisations. Formulations proposed by Woodward et al. (2003), Hawkins et al. (2008), and Jain et al. (2006) were also evaluated without event-specific adjustment. Their equations and implementation details are provided in Supplementary Methods SM3.

2.6. Generalisation of runoff initiation

Event-derived λ_{opt} values were generalised using discrete and continuous approaches. Diagnostic reconstructions quantified how well simplified formulations retained information already contained in λ_{opt} . Predictive analyses evaluated whether λ could be estimated for an unseen event using only available descriptors. Predictors were restricted to event rainfall depth P , annual potential maximum retention S , rainfall kinetic energy E , and I_{30} ; calendar month was additionally included for regime classification. Direct soil–water–content measurements were unavailable for the complete monitoring period.

The notation distinguishes formulation and application. $\lambda_{kmc,diag}$ denotes the K-means centroid assigned from an event's own λ_{opt} , whereas $\lambda_{kmc,pred}$ denotes a centroid assigned from predictors using training-fold information only. Similarly, $\lambda_{cont,diag}$ denotes a continuous estimate from a model fitted to the complete dataset, and $\lambda_{cont,pred}$ an estimate generated for a validation event by a model fitted only to the corresponding training data.

2.6.1. Regime-based representation using K-means clustering

K-means clustering (MacQueen, 1967) was applied to the one-dimensional λ_{opt} distribution. For a specified number of regimes K , events were partitioned by minimizing the within-cluster sum of squared distances:

$$\min_{CL_1, \dots, CL_K} \sum_{j=1}^K \sum_{\lambda_{opt} \in CL_j} \|\lambda_{opt} - \mu_j\|^2 \quad (3)$$

where CL_j denotes cluster j and μ_j its centroid. Candidate solutions were evaluated for $K = 3$ – 7 , using ten random initializations per fit. To avoid poorly supported regimes, a minimum cluster size of four events was imposed; smaller clusters were merged with the neighbouring cluster having the closest centroid. Final regimes were ordered from lowest to highest centroid.

For diagnostic evaluation, each λ_{opt} was replaced by the centroid of its own cluster, producing $\lambda_{kmc,diag}$, which was then used in SCS–CN calculation. This analysis measured the degree to which a limited number of abstraction states preserved the runoff-response information represented by event-specific optimisation. Because assignment used the evaluated event's own λ_{opt} , it was not considered an independent prediction.

2.6.2. Prediction of runoff-initiation regimes

Regime membership was predicted with a Random Forest classifier using P , S , E , I_{30} and calendar month through $month_{sin}$ and $month_{cos}$. Predictors were retained a priori; PCA was not used for variable selection. Prediction was evaluated by fivefold cross-validation repeated ten times. Within each training fold, K-means clustering, application of the minimum-size rule, and centroid estimation were performed using only training-event λ_{opt} values. The resulting labels were used to train the classifier. Validation events were assigned only from their descriptors; their observed runoff and λ_{opt} were not used. Each predicted class was converted to its training-fold centroid, producing $\lambda_{kmc.pred}$ for the SCS–CN calculation.

The Random Forest comprised 300 trees, a maximum depth of four, at least two events per terminal node, and inverse-frequency class weighting. Settings and cross-validation partitions were held constant across candidate K values. For each K , runoff performance was calculated once per repetition after combining predictions from the five validation folds. The retained K maximized mean cross-validated runoff NSE. Ties were resolved using the lower standard error and then the smaller K .

Five folds preserved approximately 80% of events for fitting, and repetition reduced dependence on a single partition, particularly for infrequent high-abstraction regimes. Each event therefore received one out-of-sample prediction in each repetition.

2.6.3. Interpretation and stability of the retained regimes

PCA, CART, and bootstrap resampling were applied after K selection and were strictly descriptive. PCA was fitted to standardised P , S , E , I_{30} , $month_{sin}$ and $month_{cos}$ to visualize the main gradients in predictor space and the overlap among regimes. Calendar month was encoded cyclically as $month_{sin} = \sin(2\pi \cdot month/12)$ and $month_{cos} = \cos(2\pi \cdot month/12)$, thereby preserving continuity between December and January. A constrained CART model provided a simplified threshold-based interpretation of regime membership; tree depth was limited to four, terminal nodes contained at least four events, and class weighting was applied. CART was treated as a descriptive surrogate, not as an alternative predictive model.

Regime stability was assessed with 500 non-parametric bootstrap samples. K-means clustering and the minimum-size rule were repeated for each sample. Bootstrap centroids were aligned with full-dataset centroids according to their ordered positions and distances. Stability was summarized by centroid variability and by the Adjusted Rand Index comparing bootstrap-derived and full-dataset partitions.

2.6.4. Continuous regression-based representation

As an alternative to discrete regimes, λ_{opt} was estimated continuously. The simple multiple linear model was:

$$\hat{\lambda} = a + b.P + c.S + d.E + e.I_{30} \quad (4)$$

where a is the intercept, and b , c , d , and e are fitted coefficients.

An extended linear model with pairwise interactions, a power-law model, an exponential log-linear model, and a Michaelis–Menten-type model were also tested. Candidate models were first fitted to the complete dataset to assess diagnostic reconstruction of λ_{opt} ; these estimates are denoted $\lambda_{cont.diag}$.

Predictive estimates $\lambda_{cont.pred}$ were obtained by cross-validation. All transformations and coefficients were estimated from training events only and applied unchanged to validation events. Models were compared primarily from runoff performance after application of the SCS–CN equation, because an accurate fit in λ -space does not necessarily yield accurate runoff after nonlinear transformation. Corrected Akaike Information Criterion provided a complementary measure of parsimony, and LASSO-regularized linear models were examined as a robustness check. The retained model was used for runoff-volume and peak-discharge calculations. Full equations and coefficients are reported in

Supplementary Methods SM6.

2.7. Runoff-volume and peak-discharge estimation

At the 5 min time step, the SCS–CN equation was applied to cumulative rainfall to calculate cumulative runoff depth. Successive differences yielded incremental effective rainfall, and total runoff depth was converted to volume using a catchment area of 83.84-ha. Runoff volume was calculated for all λ formulations, including the fixed values.

Peak discharge was estimated only for the event-specific λ_{opt} values and the diagnostic and predictive λ models. The 5 min effective-rainfall series was convolved with a unit hydrograph derived from the USDA–NRCS watershed-lag procedure (USDA–NRCS, 2021). The lag time was calculated using the mean catchment CN for the corresponding year and therefore could vary among years, but was identical across λ formulations for events occurring in the same year. The routing procedure was identical across λ formulations, while the unit-hydrograph timing could vary among years according to the annual mean catchment CN.

2.8. Sensitivity analysis

Sensitivity of $\lambda_{kmc.pred}$ and $\lambda_{cont.pred}$ was evaluated by perturbing annual CN and the observed runoff values used to derive λ_{opt} . CN and runoff were independently varied by -10% , -5% , 0% , $+5\%$, and $+10\%$, producing a 5×5 factorial design. Scenarios with no runoff perturbation isolated the effect of CN, scenarios with no CN perturbation isolated the effect of observed runoff, and the remaining cells represented joint perturbations.

For each scenario, S and λ_{opt} were recalculated and both predictive models were re-estimated within the same repeated fivefold cross-validation partitions. The number of regimes was fixed at five for the regime-based analysis.

Cumulative rainfall during the 3, 5, 7, and 10 days preceding each event was additionally tested as a proxy for antecedent wetness. Each window was added separately to the Random Forest predictor set, while K , classifier settings, and cross-validation partitions remained unchanged. Its contribution was assessed from changes in runoff performance, accuracy, and macro-F1 relative to the same model without antecedent rainfall. Because training samples overlapped among repetitions, paired differences were interpreted descriptively.

2.9. Event-scale sediment-yield modelling with MUSLE

Event sediment yield was estimated for events with complete suspended-sediment observations using the Modified Universal Soil Loss Equation:

$$SY = \alpha \cdot (Q \cdot q_p)^\beta \cdot K_{soil} \cdot LS \cdot C \cdot P_{USLE} \quad (5)$$

where SY is event sediment yield, Q is runoff volume, q_p is peak discharge, K_{soil} is soil erodibility, LS is the topographic factor, C is the cover-management factor, P_{USLE} is the support-practice factor, and α and β are empirical coefficients.

The K , LS , and P_{USLE} factors were treated as constant across events. The C factor varied annually and was calculated as an area-weighted catchment value from annual crop proportions and crop-specific values. Factor values and spatial calculations are reported in the Supplementary Material SM4.

MUSLE was applied with either modelled or observed hydrological inputs. Modelled runoff volume and peak discharge were obtained from the common SCS–CN and unit-hydrograph calculations for each λ formulation. In the observed-input configuration, measured runoff volume and peak discharge were used directly. Predictions were compared with observed event sediment yield.

The exponent β was fixed at 0.56, corresponding to the historical

MUSLE formulation of Williams (1972, 1975), and only the multiplicative coefficient α was calibrated. Fixing β limited flexibility and reduced compensation between the runoff-energy exponent and errors in hydrological inputs. For each input configuration, α was calibrated on training events and applied unchanged to validation events. This allowed configurations to be compared under a common exponent while accounting for systematic differences in the magnitude of the runoff-energy term.

2.10. Cross-validation and performance assessment

Model performance was assessed separately for event runoff volume, peak discharge, and sediment yield by comparing modelled and observed values using Nash–Sutcliffe efficiency (NSE), Kling–Gupta efficiency (KGE), percent bias (PBIAS), and relative root mean square error (RRMSE). NSE was the primary criterion for comparing runoff predictions and selecting K ; the other metrics described overall agreement, systematic bias, and relative error.

Predictive runoff performance was evaluated by fivefold cross-validation repeated ten times, using identical partitions for competing formulations. For the regime-based model, K-means fitting, minimum-size enforcement, centroid estimation, and Random Forest training were repeated within each training fold. For the continuous model, all transformations and coefficients were estimated from training data only. Predictions from the five validation folds were combined within each repetition, after which NSE, KGE, PBIAS, and RRMSE were calculated once. Reported predictive metrics are the arithmetic means of the ten repetition-specific values; standard deviation and standard error describe variability among partitions.

Diagnostic formulations were evaluated separately. The λ_{opt} , $\lambda_{kmc,diag}$ and $\lambda_{cont,diag}$ values were derived from the complete hydrological dataset and therefore produced one runoff series and one value per performance metric; they were not averaged across repetitions.

MUSLE was evaluated by fivefold cross-validation on the 46-event sediment subset, using identical validation events across hydrological input configurations. The coefficient α was calibrated from training events only. Sensitivity metrics were likewise calculated within each

repetition and averaged across repetitions. Classification performance was assessed using accuracy and macro-F1, the unweighted mean of class-specific F1 scores. Repetition-specific differences were summarized descriptively because repeated cross-validation involved overlapping training samples.

3. Results

Hydrological results are reported for the 154 rainfall–runoff events retained in the processed dataset supplied by the laboratory. Sediment-yield results are reported for the 46 events with complete and synchronized sediment observations and all inputs required for MUSLE. Diagnostic configurations, which use information derived from the observed runoff response of the evaluated events, are distinguished from predictor-based configurations evaluated out of sample.

3.1. Event-scale variability of the optimised initial abstraction ratio

The event-specific λ_{opt} varied strongly across the 154 events (Fig. 5). The distribution was right-skewed: most events had low abstraction ratios, while a smaller number required substantially higher values to reproduce observed runoff. Because λ_{opt} was obtained from the runoff response of each event, it represents an effective event-scale runoff-initiation indicator rather than an independently predicted parameter.

The median λ_{opt} was 0.056 and the mean was 0.076. The interquartile range was 0.030–0.101, and the central 80% of values ranged from 0.016 to 0.161. The observed variability therefore reflected broad event-to-event differences rather than only a few extreme values. Event-specific values are reported in Supplementary Material SM5 (Table SM7).

3.2. Benchmark evaluation of fixed and literature-based formulations

Fixed and published initial abstraction formulations showed limited ability to reproduce observed runoff when implemented in the SCS–CN model (Table 2). The standard $\lambda = 0.20$ formulation generated non-zero runoff for only 20 of the 154 observed runoff events and produced NSE

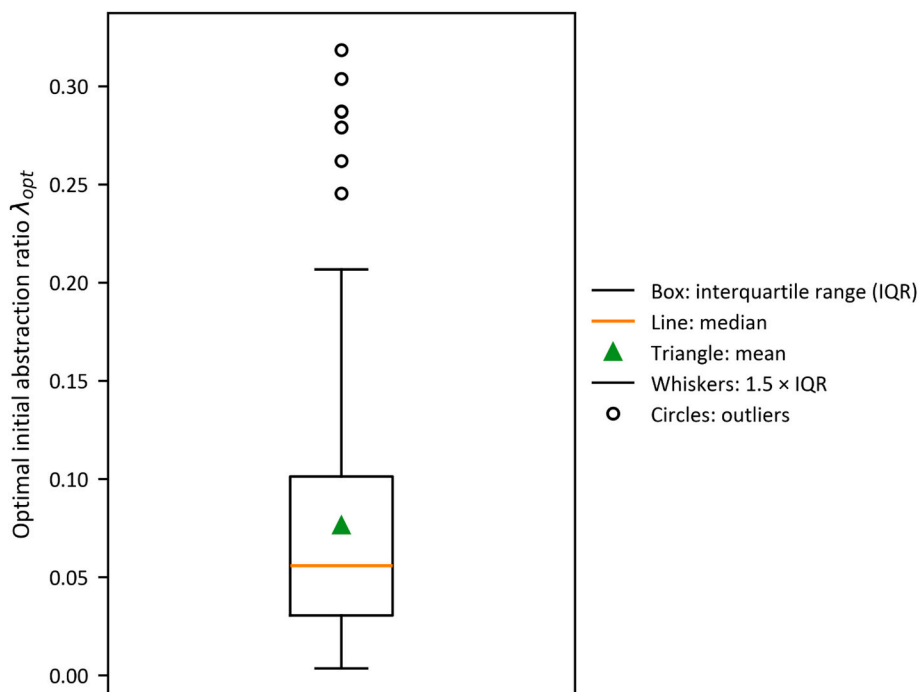


Fig. 5. Distribution of event-specific optimised initial abstraction ratios (λ_{opt}) for the 154 rainfall–runoff events. The box spans the interquartile range (IQR), the line and triangle denote the median and mean, respectively, whiskers extend to $1.5 \times \text{IQR}$, and circles denote outliers.

Table 2

Performance of fixed and literature-based initial abstraction ratio (λ) formulations for event runoff-volume estimation using the SCS-CN model. Metrics were calculated over all 154 rainfall-runoff events, including events with zero simulated runoff. “Runoff predicted” denotes the number of events for which each formulation generated non-zero runoff.

Formulation	λ	Runoff predicted (#)	NSE	KGE	PBIAS (%)	RRMSE (%)
SCS-CN	0.20	20	0.13	0.39	48.81	188.48
	0.05	130	-7.00	-2.12	-217.27	572.11
	0.01	154	-13.83	-4.04	-412.01	779.09
Woodward	0.05	89	-0.87	0.00	-45.18	276.41
Hawkins	0.05	101	-1.84	-0.47	-82.82	341.06
Jain	0.30	154	-9.59	-3.39	-374.05	658.21

= 0.13, KGE = 0.39, PBIAS = 48.81%, and RRMSE = 188.48%, indicating substantial underestimation.

Lower fixed ratios generated runoff more frequently but strongly overestimated runoff volume. With $\lambda = 0.05$, runoff was simulated for 130 events and PBIAS reached -217.27%; with $\lambda = 0.01$, runoff was simulated for all events and PBIAS reached -412.01%. Both formulations had strongly negative NSE and KGE values. The Woodward, Hawkins, and Jain parameterisations also performed poorly without local adjustment. Woodward was the least unfavourable published formulation, but its NSE remained negative and its KGE was approximately zero.

All metrics were calculated over the full set of 154 events, including events with zero simulated runoff. Thus, the “Runoff predicted” column in Table 2 indicates simulated runoff-initiation frequency, not sample size. Overall, no fixed or published formulation reproduced the full range of event responses, supporting the use of event-dependent representations.

3.3. Regime-based representation of runoff initiation

3.3.1. Diagnostic simplification of event-scale runoff initiation

K-means clustering was applied to the λ_{opt} distribution for candidate solutions with three to seven regimes. In the diagnostic configuration, each event was assigned to a regime based on its own λ_{opt} , which was then replaced by the corresponding centroid $\lambda_{kmc,diag}$. This represents an in-sample simplification rather than an independent prediction.

Diagnostic runoff performance improved as the number of regimes increased (Table 3). NSE rose from 0.63 for three regimes to 0.89 for four and 0.94 for five. Six and seven regimes both yielded NSE values of about 0.96, but the marginal gain beyond five regimes was small. The five-regime solution produced NSE = 0.94, KGE = 0.89, PBIAS = 7.54%, and RRMSE = 51.33%, retaining most of the runoff-volume information contained in the event-specific values with moderate overall underestimation.

Diagnostic performance was not used alone to select the number of regimes because in-sample fit necessarily improves as centroids are added. The retained number was therefore selected from the cross-

Table 3

Diagnostic runoff-volume performance of candidate K-means regime structures after application of the SCS-CN model. Event-specific optimised initial abstraction ratios (λ_{opt}) were replaced by the centroid of the regime identified from the event's own λ_{opt} , producing $\lambda_{kmc,diag}$. Performance was evaluated against observed runoff for the 154 rainfall-runoff events.

K	NSE	KGE	PBIAS (%)	RRMSE (%)
3	0.63	0.56	22.34	122.45
4	0.89	0.85	9.03	66.23
5	0.94	0.89	7.54	51.33
6	0.96	0.91	6.03	41.96
7	0.96	0.86	7.50	38.03

validated predictor-assigned formulation.

3.3.2. Predictive selection and assignment of runoff-initiation regimes

Predictive regime assignment was evaluated with a Random Forest classifier. Within each cross-validation fold, K-means clustering, centroid estimation, and classifier fitting were performed using training events only. Validation events were classified from rainfall depth, potential maximum retention, rainfall kinetic energy, maximum 30-min rainfall intensity, $\text{month}_{\sin}$ and $\text{month}_{\cos}$. The predicted class was converted to its training-fold centroid $\lambda_{kmc,pred}$.

Cross-validated runoff performance was substantially weaker than the diagnostic reconstruction for all candidate regime numbers (Table 4). Mean NSE ranged from 0.13 to 0.21, indicating that the regimes summarized observed runoff-initiation structure effectively but could only be partly inferred from the available descriptors. The highest mean NSE was obtained with five regimes, at 0.21, closely followed by six regimes, at 0.20. Mean NSE values were 0.19, 0.13, and 0.14 for three, four, and seven regimes, respectively. The five-regime structure was therefore retained because it maximized the primary selection criterion without the additional complexity of larger solutions. Because the same cross-validation procedure was used both to select K and to estimate the performance of the selected model, the reported NSE should be interpreted as an internal model-selection estimate that may be slightly optimistic, rather than as a fully independent estimate of predictive performance.

The contrast between $\lambda_{kmc,diag}$ and $\lambda_{kmc,pred}$ is central: the former measures how well a limited set of centroids summarizes runoff-initiation variability already contained in observed event responses, whereas the latter evaluates whether the appropriate centroid can be assigned without knowledge of observed runoff.

3.3.3. Characteristics and stability of the retained regimes

The retained solution had centroids of 0.020, 0.058, 0.112, 0.177, and 0.283 (Table 5). The first two regimes contained 47 and 59 events and together represented 68.8% of the dataset. Regime 3 contained 29 events, while regimes 4 and 5 contained 12 and 7 events. Overall, 87.7% of events belonged to the three lowest-abstraction regimes, leaving relatively few observations for training the highest-abstraction classes.

Bootstrap centroid means remained close to the full-dataset values. Coefficients of variation ranged from 6.2% to 17.4%, with the highest value for the lowest-abstraction regime. Event assignments were also comparatively stable, with a mean Adjusted Rand Index of 0.85 ± 0.15 . These results indicate a reproducible partition within the monitored dataset, although centroid values and frequencies remain catchment-specific.

3.3.4. Hydro-meteorological interpretation of the retained regimes

The first two PCA axes explained 46.4% and 20.7% of standardised predictor variance, respectively (Fig. 6). Rainfall depth, kinetic energy, and maximum 30-min intensity contributed mainly to the first axis, whereas potential maximum retention and seasonal timing contributed more strongly to the second.

Table 4

Cross-validated runoff-volume performance of Random Forest-assigned runoff-initiation regimes. For each candidate number of regimes (K), K-means fitting, centroid estimation, and Random Forest training were performed exclusively within the training folds. Predicted regime membership was converted into the corresponding training-derived centroid ($\lambda_{kmc,pred}$). Metrics are means across ten repetitions of fivefold cross-validation.

K	NSE	KGE	PBIAS (%)	RRMSE (%)
3	0.19	0.54	-12.86	180.30
4	0.13	0.55	-7.38	186.29
5	0.21	0.55	-17.65	179.45
6	0.20	0.54	-17.34	180.17
7	0.14	0.49	-23.84	186.27

Table 5

Centroids, event frequencies, and bootstrap stability of the retained five-regime K-means solution. λ_{kmc} denotes the regime centroid. Bootstrap statistics were obtained from 500 replicates, and overall event-assignment consistency was assessed using the Adjusted Rand Index (ARI).

Regime	Centroid λ_{kmc}	Event count n	Frequency (%)	Bootstrap centroid		
				mean	SD	CV (%)
1	0.020	47	30.5	0.021	0.004	17.414
2	0.058	59	38.3	0.058	0.006	10.118
3	0.112	29	18.8	0.109	0.007	6.244
4	0.177	12	7.8	0.177	0.013	7.587
5	0.283	7	4.5	0.279	0.033	11.715

Overall bootstrap assignment stability: ARI = 0.85 ± 0.15 .

Notes: standard deviation (SD); coefficient of variation (CV).

Rainfall forcing generally increased from low- to high-abstraction regimes (Table 6). Median rainfall depth rose from 4.81 mm in regime 1 to 28.91 mm in regime 5, and median I_{30} increased from 2.98 to 13.16 mm.h⁻¹. Runoff efficiency did not follow the same pattern. Regime 1 had the highest median runoff coefficient, whereas regime 5 combined the largest rainfall inputs with the lowest median runoff coefficient. Regime 4 showed the greatest variability in runoff efficiency.

CART identified rainfall depth as the main first-order discriminator, with rainfall intensity, potential retention, and month providing secondary contrasts (Fig. 7). However, substantial overlap remained among intermediate regimes. The five clusters are therefore interpreted as recurrent effective runoff-response patterns rather than independent physical catchment states.

3.4. Continuous prediction of runoff initiation from hydro-meteorological descriptors

The continuous formulations showed contrasting performance for estimating λ_{opt} (Table 7). The exponential model performed poorly in calibration and cross-validation. The simple linear, interaction-based linear, power-law, and Michaelis–Menten-type models reproduced a substantial part of the event-scale variability.

Under fivefold cross-validation, the interaction-based linear and power-law models achieved the highest NSE, both at 0.79. The power-law model produced KGE = 0.88, PBIAS = 5.17%, and RRMSE = 38.95%, whereas the interaction model produced KGE = 0.86, PBIAS = 0.53%, and RRMSE = 39.39%. The simple linear model was only slightly weaker, with NSE = 0.78, KGE = 0.85, PBIAS = 0.17%, and RRMSE = 39.76%. The Michaelis–Menten-type model yielded NSE = 0.76.

Within the original response space, AICc was −668.26 for the interaction-based linear model, −645.95 for the simple linear model, and −635.88 for the Michaelis–Menten-type model. Values for the power-law and exponential formulations were calculated in log-transformed response space and were therefore not directly comparable.

Although the interaction model had the lowest AICc among models fitted in the original response space, most interaction coefficients were weakly supported and the model generated negative predictions for five events. The simple linear model was therefore retained because it offered similar predictive performance, a more parsimonious coefficient structure, near-zero mean bias, and more consistent hydrological behaviour. LASSO-regularized variants did not change this selection. Hydrological performance was evaluated separately because good prediction in λ -space does not necessarily translate into accurate runoff

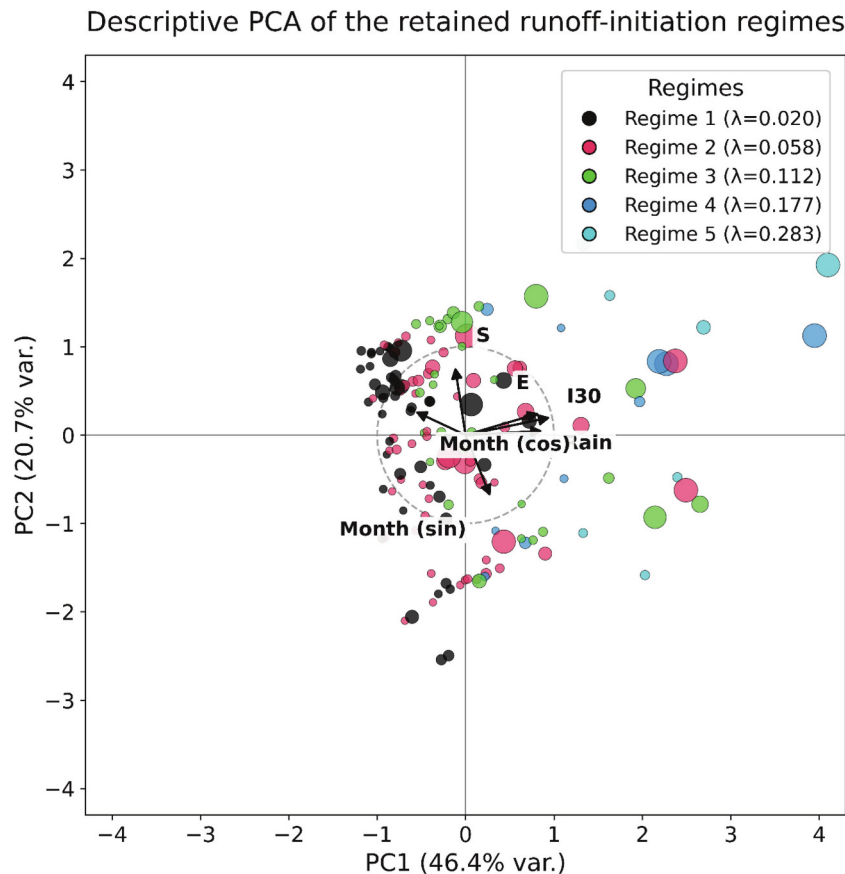


Fig. 6. Principal component analysis (PCA) of standardised hydro-meteorological descriptors for the retained five-regime K-means solution. Events are coloured according to their diagnostic runoff-initiation regime, point size is proportional to observed runoff depth (mm), and arrows indicate predictor loadings. Rain denotes event rainfall depth, I_{30} the maximum 30-min rainfall intensity, E rainfall kinetic energy, and S potential maximum retention. Calendar month was represented cyclically using sine and cosine components.

Table 6

Descriptive hydro-meteorological characteristics of the retained five runoff-initiation regimes. Continuous variables are reported as median [interquartile range]. λ_{kmc} denotes the regime centroid, I_{30} the maximum 30-min rainfall intensity, E rainfall kinetic energy, and S potential maximum retention. The runoff coefficient was calculated as observed runoff depth divided by event rainfall depth. Regimes were derived from event-specific λ_{opt} values and represent effective response patterns rather than independent physical catchment classes.

Regime	λ_{kmc}	Events (#)	Rainfall (mm)	I_{30} (mm.h ⁻¹)	E (MJ.ha ⁻¹)	S (mm)	Runoff coefficient (%)	Descriptive response pattern
1	0.02	47	4.81 [3.68–6.90]	2.98 [2.23–4.57]	0.65 [0.50–0.88]	94.67 [94.48–94.67]	1.84 [1.06–3.08]	Low rainfall, low abstraction, comparatively high runoff efficiency
2	0.058	59	7.83 [6.04–10.79]	5.20 [3.26–8.68]	1.20 [0.85–1.66]	94.48 [89.84–94.67]	0.77 [0.25–1.95]	Low-to-moderate rainfall and reduced runoff efficiency
3	0.112	29	13.36 [11.55–15.18]	5.68 [3.94–10.04]	1.83 [1.59–2.33]	94.48 [90.41–94.48]	0.49 [0.13–1.46]	Intermediate rainfall forcing and low runoff efficiency
4	0.177	12	19.13 [18.55–24.73]	8.34 [5.07–12.23]	3.01 [2.57–5.17]	94.57 [91.72–94.67]	0.84 [0.15–2.74]	High rainfall forcing and heterogeneous runoff response
5	0.283	7	28.91 [27.11–33.54]	13.16 [10.22–18.71]	5.73 [5.00–6.30]	92.35 [88.25–93.51]	0.40 [0.28–0.84]	Highest rainfall forcing and low runoff efficiency

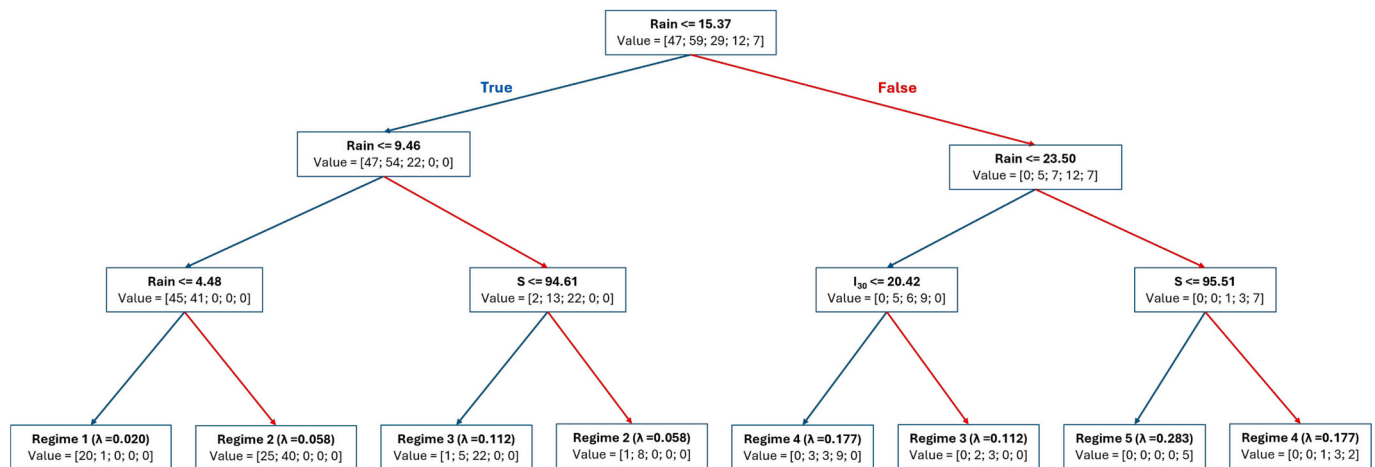
CART surrogate – K = 5

Fig. 7. Simplified classification and regression tree (CART) used for post hoc interpretation of the five runoff-initiation regimes. The tree was limited to four levels and was not used for model selection or predictive evaluation. Rain denotes event rainfall depth (mm), S potential maximum retention (mm), and I_{30} maximum 30-min rainfall intensity (mm h⁻¹). “Value = [...]” gives the number of events belonging to each regime within a node, reported in regime order (1–5).

Table 7

Calibration and repeated fivefold cross-validated performance of candidate continuous formulations for estimating the event-specific initial abstraction ratio (λ_{opt}). Cross-validated metrics are means across ten repetitions. AICc values were calculated in each model's fitted response space and are directly comparable only among models fitted in the same response space.

Model	–	Calibration				5-fold				AICc
		NSE	KGE	PBIAS (%)	RRMSE (%)	NSE	KGE	PBIAS (%)	RRMSE (%)	
LM (simple)		0.80	0.85	0.00	37.68	0.78	0.85	0.17	39.76	–645.95
LM (interactions)		0.85	0.89	0.00	33.55	0.79	0.86	0.53	39.39	–668.26
Power-law		0.80	0.87	6.14	38.03	0.79	0.88	5.17	38.95	232.22
Exponential		0.26	0.57	2.60	73.11	0.02	0.45	0.19	84.56	275.99
Michaelis–Menten		0.79	0.85	0.33	38.94	0.76	0.84	1.05	41.51	–635.88

after nonlinear transformation by the SCS–CN equation.

Full details of the tested regression formulations, coefficient estimates, and regularized variants are provided in Supplementary Material SM6 (Table SM8 and Table SM9).

3.5. Runoff-volume and peak-discharge prediction

Hydrological performance differed strongly between diagnostic and predictive configurations (Table 8). As expected, λ_{opt} reproduced runoff volume almost exactly, with NSE and KGE close to 1.00, PBIAS = 0.33%, and RRMSE = 2.36%. The diagnostic five-regime representation

Table 8

Diagnostic and predictive runoff-volume and peak-discharge performance of the runoff-initiation formulations. λ_{opt} denotes the event-specific optimised abstraction ratio; $\lambda_{kmc,diag}$ and $\lambda_{cont,diag}$ denote the regime-based and continuous full-data diagnostic estimates, respectively; and $\lambda_{kmc,pred}$ and $\lambda_{cont,pred}$ denote the corresponding out-of-sample estimates. Diagnostic metrics were calculated once for the complete dataset, whereas predictive metrics are means across ten repetitions of fivefold cross-validation.

	Runoff volume				
	Diagnostic			Prediction	
	λ_{opt}	$\lambda_{kmc,diag}$	$\lambda_{cont,diag}$	$\lambda_{kmc,pred}$	$\lambda_{cont,pred}$
NSE	1.00	0.94	0.48	0.21	0.40
KGE	1.00	0.89	0.41	0.55	0.33
PBIAS (%)	0.33	7.54	18.89	−17.65	23.30
RRMSE (%)	2.36	51.33	146.46	179.45	156.93
	Peak discharge				
	Diagnostic			Prediction	
	λ_{opt}	$\lambda_{kmc,diag}$	$\lambda_{cont,diag}$	$\lambda_{kmc,pred}$	$\lambda_{cont,pred}$
NSE	0.71	0.67	0.41	−0.26	0.34
KGE	0.72	0.79	0.41	0.40	0.58
PBIAS (%)	17.76	11.15	22.27	5.89	23.22
RRMSE (%)	90.44	96.95	128.51	191.91	139.44

retained most of this information, with NSE = 0.94 and KGE = 0.89. By contrast, the full-data continuous reconstruction produced NSE = 0.48, KGE = 0.41, PBIAS = 18.89%, and RRMSE = 146.46%. Thus, regime centroids provided the stronger diagnostic simplification of the event-derived runoff response.

Both predictive approaches performed less well than their diagnostic counterparts. The continuous formulation produced lower squared errors, with NSE = 0.40 and RRMSE = 156.93%, compared with NSE = 0.21 and RRMSE = 179.45% for the predictor-assigned regimes. However, the regime-based model had higher KGE, at 0.55 compared with 0.33, and lower absolute PBIAS, at −17.65% compared with 23.30%. The two formulations also showed opposite aggregate biases: the regime model underestimated total runoff, whereas the continuous model overestimated it.

Peak discharge was reproduced less accurately than runoff volume, but the diagnostic results nevertheless showed substantial skill. The event-specific λ_{opt} formulation yielded NSE = 0.71, KGE = 0.72, PBIAS = 17.76%, and RRMSE = 90.44%. Replacing λ_{opt} with the five-regime centroids retained most of this peak-discharge performance, with NSE = 0.67, KGE = 0.79, PBIAS = 11.15%, and RRMSE = 96.95%. The diagnostic continuous formulation was weaker, with NSE = 0.41, KGE = 0.41, PBIAS = 22.27%, and RRMSE = 128.51%. Thus, the regime representation preserved not only runoff-volume information but also much of the diagnostic peak-discharge response.

Under predictive conditions, the continuous model again performed better for peak discharge, with NSE = 0.34, KGE = 0.58, PBIAS = 23.22%, and RRMSE = 139.44%. The predictor-assigned regime model produced NSE = −0.26 and RRMSE = 191.91%, despite a smaller aggregate bias. Overall, the five-regime approach provided a strong diagnostic summary of both runoff volume and peak discharge, but it did not outperform the continuous model out of sample. The marked decline from diagnostic to predictive peak-discharge performance indicates that identifying the appropriate runoff-initiation response for unseen events remains a major limitation.

3.6. Sensitivity analyses of the predictive formulations

Sensitivity was evaluated for 25 combinations of CN and observed-runoff perturbations (Table 9). The continuous model was comparatively stable, with cross-validated runoff NSE ranging from 0.36 to 0.42 around the reference value of 0.40. CN perturbations alone produced almost no change, whereas increasing the runoff values used to derive λ_{opt} generally reduced NSE. The model was therefore more sensitive to the imposed perturbations in observed runoff than to moderate changes

Table 9

Sensitivity of cross-validated runoff-volume NSE to joint perturbations of Curve Number (CN) and observed runoff for the continuous linear and five-regime models. Values are means across ten repetitions of fivefold cross-validation. For each scenario, λ_{opt} and the corresponding predictive model were re-estimated within the training folds. The central cell is the unperturbed reference configuration, and the number of regimes was fixed at five for the regime-based model.

	Linear model					
	CN perturbation					
		−10%	−5%	0%	5%	10%
Runoff perturbation	−10%	0.41	0.41	0.41	0.42	0.42
	−5%	0.41	0.41	0.41	0.41	0.41
	0%	0.40	0.40	0.40	0.40	0.40
	5%	0.38	0.39	0.39	0.39	0.39
	10%	0.36	0.37	0.37	0.37	0.37
	Regime-based model					
	CN perturbation					
		−10%	−5%	0%	5%	10%
Runoff perturbation	−10%	0.27	0.27	0.27	0.26	0.25
	−5%	0.27	0.25	0.28	0.23	0.27
	0%	0.17	0.21	0.21	0.28	0.24
	5%	0.19	0.26	0.21	0.23	0.21
	10%	0.13	0.16	0.14	0.22	0.23

in CN.

The five-regime model showed a broader and less regular response, with NSE ranging from 0.13 to 0.28 around the reference value of 0.21. No monotonic pattern emerged because perturbations could alter λ_{opt} regime boundaries, centroid values, classifier training, and event assignments.

Adding 3-day antecedent rainfall increased mean runoff NSE from 0.205 to 0.249, but improvement occurred in only five of ten repetitions and the descriptive 95% interval of differences included zero, ranging from −0.008 to 0.096. Accuracy and macro-F1 also decreased slightly, from 0.643 to 0.629 and from 0.584 to 0.577, respectively.

The 10-day window produced performance close to the reference model, while the 5- and 7-day windows reduced mean NSE to 0.047 and 0.120. None of the tested windows consistently improved both runoff prediction and classification, so antecedent rainfall was not retained.

Overall, the continuous formulation maintained higher and more stable predictive performance across the tested perturbations. Scenarios with higher NSE than the reference should be interpreted as sensitivity outcomes, not as evidence that perturbed inputs were more hydrologically realistic.

3.7. Event-scale sediment-yield prediction with MUSLE

MUSLE performance depended strongly on the hydrological inputs used (Table 10). The configuration based on observed runoff volume and peak discharge performed best, with cross-validated NSE = 0.66 and KGE = 0.56. Using hydrological variables derived from λ_{opt} reduced NSE to 0.46, showing that errors introduced during hydrological modelling degraded sediment-yield prediction.

For the observed-input configuration, calibration NSE was 0.72 and decreased moderately to 0.66 under cross-validation. The corresponding values for the λ_{opt} -based configuration were 0.54 and 0.46.

Among diagnostic configurations, the five-regime formulation clearly outperformed the continuous reconstruction. Cross-validated NSE and KGE were 0.48 and 0.62 with $\lambda_{kmc,diag}$ compared with 0.10 and 0.12 with $\lambda_{cont,diag}$. The diagnostic regime formulation also maintained a relatively small bias and performed close to the λ_{opt} -based configuration. Its NSE decreased only from 0.52 in calibration to 0.48 under cross-validation, whereas the diagnostic continuous model remained weak in both cases.

Predictive sediment-yield performance was poor for both

Table 10

Calibration and fivefold cross-validated performance of MUSLE for predicting event sediment yield for the 46 events with complete observed sediment-yield data and required model inputs. All performance metrics compare MUSLE-predicted event sediment yield with observed event sediment yield. MUSLE was evaluated using either observed runoff volume (Q) and peak discharge (q_p), or Q and q_p simulated using λ_{opt} , $\lambda_{kmc,diag}$, $\lambda_{cont,diag}$, $\lambda_{kmc,pred}$, or $\lambda_{cont,pred}$. The runoff-energy exponent β was fixed at 0.56, and the multiplicative coefficient α was calibrated separately for each hydrological-input configuration. Cal. denotes global calibration.

	SY with observed Q and q_p		SY with Q and q_p from λ_{opt}	
α	1.64	1.63	1.25	1.25
β		0.56		0.56
	Cal.	5-fold	Cal.	5-fold
NSE	0.72	0.66	0.54	0.46
KGE	0.57	0.56	0.57	0.53
PBIAS (%)	34.05	32.01	15.72	15.75
RRMSE (%)	136.59	151.81	175.21	191.14
	SY with Q and q_p from $\lambda_{kmc,diag}$		SY with Q and q_p from $\lambda_{cont,diag}$	
α	1.09	1.10	1.03	1.04
β		0.56		0.56
	Cal.	5-fold	Cal.	5-fold
NSE	0.52	0.48	0.13	0.10
KGE	0.60	0.62	0.11	0.12
PBIAS (%)	1.70	5.79	-7.45	-5.52
RRMSE (%)	179.09	187.46	242.05	245.39
	SY with Q and q_p from $\lambda_{kmc,pred}$		SY with Q and q_p from $\lambda_{cont,pred}$	
α	1.09	1.10	1.03	1.04
β		0.56		0.56
	Cal.	5-fold	Cal.	5-fold
NSE	-0.02	-0.03	0.04	0.01
KGE	-0.12	-0.12	0.04	0.05
PBIAS (%)	-38.92	-37.76	-5.92	-4.11
RRMSE (%)	261.21	263.11	253.88	257.51

approaches. The predictor-assigned regime formulation produced NSE = -0.03, while the predictive continuous formulation produced NSE = 0.01. The regime-based configuration overestimated sediment yield overall, with PBIAS = -37.76%, whereas the continuous formulation had a smaller aggregate bias, with PBIAS = -4.11%. Nevertheless, RRMSE remained similarly high, at 263.11% and 257.51%, respectively. A small aggregate bias therefore did not imply accurate event-level prediction.

The fitted MUSLE coefficient changed little between global calibration and cross-validation. Performance loss therefore resulted mainly from errors in runoff volume and peak discharge rather than instability in the calibrated coefficient. These hydrological errors were amplified through the nonlinear runoff-energy term.

4. Discussion

4.1. Event-scale variability and interpretation of effective runoff-initiation regimes

The analysis of 154 rainfall-runoff events showed that runoff initiation could not be represented adequately by a single initial abstraction ratio. Event-specific λ_{opt} values varied substantially among events, and neither fixed ratios nor published formulations reproduced the complete range of observed runoff responses. The classical $\lambda = 0.20$ formulation generated runoff for only a limited proportion of the observed runoff-producing events, whereas lower fixed values increased runoff-initiation frequency but strongly overestimated runoff volume. The difficulty was therefore not resolved by selecting a universally lower abstraction ratio.

This result agrees with studies showing that the SCS-CN initial

abstraction ratio is not directly transferable across catchments and event conditions (Baltas et al., 2007; Fu et al., 2011; Caletka et al., 2020; Hawkins and Woodward, 2019). In cultivated catchments, runoff response may change rapidly with antecedent wetness, sealing, crusting, roughness, crop development, tillage, residue cover, and runoff-pathway organization. Within the present structure, λ_{opt} should therefore be interpreted as an effective event-response indicator rather than a physically independent parameter.

This interpretation is particularly important because λ_{opt} was derived conditionally on annually parameterised Curve Number values. Part of its variability may therefore compensate for event-scale changes in catchment state that were not represented by the annual CN parameterisation. The optimised values describe the effective abstraction required by the adopted SCS-CN structure to reproduce observed runoff and should not be interpreted independently of that structure.

The retained five-regime partition provided a stable and parsimonious representation of the λ_{opt} distribution. Rainfall depth, kinetic energy, and maximum 30-min intensity increased from the lowest- to the highest-abstraction regimes, but runoff efficiency did not. The lowest-abstraction regime combined relatively small rainfall events with the highest median runoff coefficient, whereas the highest-abstraction regime combined the largest rainfall inputs with comparatively low runoff efficiency.

PCA and CART supported rainfall forcing as the main first-order discriminator among regimes, with potential maximum retention and seasonal timing providing secondary contrasts. Substantial overlap remained, particularly among the intermediate regimes. The clusters were therefore not determined solely by storm magnitude and could not be assigned uniquely to specific physical catchment conditions.

The five regimes should thus be interpreted as recurrent effective runoff-response patterns rather than as five independent physical states. Direct soil-water-content measurements at or immediately before event onset were not available for the complete monitoring period. Event-specific information on crop stage, tillage, crusting, surface roughness, vegetation, and crop-residue cover was also unavailable consistently. Because soil-surface and crop-state observations were unavailable, no regime could be attributed uniquely to a specific combination of wetness, crusting, crop stage or connectivity. These unresolved state variables may explain part of the overlap among regimes and their limited physical attribution.

4.2. Diagnostic structure, predictive performance, and validation design

A central result of this study is the contrast between diagnostic representation and out-of-sample prediction. When events were assigned to K-means regimes using their event-derived λ_{opt} , the five regime centroids preserved most of the runoff-volume information, with a diagnostic NSE of 0.94. This preservation extended to peak discharge: $\lambda_{kmc,diag}$ achieved NSE = 0.67 and KGE = 0.79, compared with NSE = 0.71 and KGE = 0.72 for λ_{opt} . Despite higher relative errors for peak discharge, the regime centroids retained much of the event-derived information relevant to both runoff volume and hydrograph magnitude.

This strong diagnostic performance did not translate into equivalent predictive performance. When regime membership was inferred from hydro-meteorological descriptors without using the validation event's runoff response, cross-validated NSE decreased to 0.21 for runoff volume and -0.26 for peak discharge. A recurrent regime structure therefore exists in the monitored responses, but the available predictors were insufficient to identify the appropriate regime reliably for new events.

The continuous formulation showed the opposite balance. It reconstructed runoff volume and peak discharge less effectively in the diagnostic analysis, with NSE values of 0.48 and 0.41, compared with 0.94 and 0.67 for the five-regime formulation. However, it produced stronger out-of-sample predictions, reaching NSE = 0.40 for runoff volume and

0.34 for peak discharge. The regime-based approach was therefore more informative diagnostically, whereas the continuous model offered greater predictive utility with the available descriptors.

This difference partly reflects the additional classification step required by the regime-based approach. An incorrect assignment replaces the estimated abstraction ratio with another regime's centroid and may cause an abrupt change in simulated runoff because of the nonlinear SCS-CN response. The continuous model instead produces gradual changes in λ without introducing a separate classification error.

The perturbation analysis supported this interpretation. The continuous formulation maintained a comparatively narrow range of runoff performance across the tested CN and observed-runoff perturbations. The regime-based response was broader and less regular because perturbations could affect event-specific targets, regime boundaries, centroid values, classifier training, and predicted assignments. The continuous formulation was consequently more robust to the range of systematic input perturbations tested here.

Adding cumulative rainfall over the 3, 5, 7, and 10 days preceding each event did not consistently improve the Random Forest-assigned regime formulation. The 3-day window produced a modest increase in mean runoff NSE, but only in half of the cross-validation repetitions and without improving classification accuracy or macro-F1. Longer windows produced similar or lower runoff performance. Fixed-window antecedent rainfall was therefore excluded from the final predictor set.

This does not imply that antecedent wetness is unimportant. Cumulative rainfall is an indirect proxy that does not explicitly represent drainage, evapotranspiration, seasonal vegetation, soil hydraulic properties, or spatial variations in water storage. Pre-event soil water content or a continuously updated soil-water-storage indicator could represent initial catchment conditions more directly, although its incremental value would need to be demonstrated through the same out-of-sample validation.

Developing the models with the 108 events lacking complete sediment observations and reserving the 46 sediment events as a test set was not retained because sediment-data availability was neither randomized nor hydrologically independent. Some excluded events occurred under high-rainfall or high-runoff conditions, and removing them would have reduced the information available for defining infrequent high-abstraction regimes. Repeated cross-validation across all 154 rainfall-runoff events ensured out-of-sample evaluation while preserving a larger and more diverse training set.

4.3. Hydrological routing, connectivity, and downstream effects on peak discharge and sediment yield

Peak discharge was reproduced less accurately than runoff volume, although the diagnostic results indicate that the framework captured a substantial proportion of peak-flow variability. The λ_{opt} formulation achieved NSE = 0.71 and KGE = 0.72, while $\lambda_{kmc,diag}$ retained similar performance, with NSE = 0.67 and KGE = 0.79. The continuous diagnostic formulation was weaker, with NSE = 0.41 and KGE = 0.41. The remaining relative errors and positive biases nevertheless show that hydrograph magnitude was not reproduced as closely as runoff volume. Runoff initiation was therefore not the only source of peak-discharge error: the simplified representation of the timing, spatial origin, and synchronization of runoff contributions also affected the simulated hydrograph.

Peak discharge was estimated using an event-invariant unit hydrograph with a watershed lag derived from the longest hydraulic flow path. Although this provided a consistent and parsimonious comparison of runoff-initiation formulations, it reduced a spatially distributed transfer process to a single pathway and travel time. Combined with the lumped catchment-scale effective rainfall generated by SCS-CN, the framework could not represent event-specific changes in contributing areas, pathway activation, or travel-time distributions.

The limitation is therefore not a failure to recognize connectivity, but

the difficulty of representing it within parsimonious structures. Neither SCS-CN nor a single watershed lag identifies which areas generate runoff, how they connect to the drainage axis, or whether their contributions reach the outlet simultaneously. This is particularly relevant in an ephemeral drainage network, where hedges, field boundaries, depressions, roughness, crop residues, wheel tracks, and temporary obstructions may store, redirect, concentrate, or delay runoff (Bracken and Croke, 2007; Bracken et al., 2015; Baartman et al., 2020).

For an equivalent runoff volume, synchronized contributions may generate a sharp peak, whereas progressively arriving contributions produce a lower and broader hydrograph. Residual peak-discharge errors, particularly the marked deterioration under predictive conditions, probably reflect limitations in the representation of both runoff generation and transfer. Better runoff-initiation prediction should reduce peak-flow prediction errors, but further improvement may remain limited while routing relies on an event-invariant travel-time structure.

Spatially distributed routing could provide a more suitable framework. Pixel-based travel-time, isochrone, or distributed unit-hydrograph methods, including HIDROPIXEL-type approaches, can combine time-dependent contributions from individual grid cells or contributing areas (Kull and Feldman, 1998; Costa et al., 2019). These methods would represent runoff origin and synchronization more explicitly, although assumptions or observations would still be required for active areas, pathway activation, velocity, roughness, and surface storage.

MUSLE performed best when observed runoff volume and peak discharge were used, confirming the importance of accurate hydrological inputs. However, substantial event-level errors remained even in this configuration, showing that sediment-yield prediction errors cannot be attributed solely to errors in the hydrological inputs. Sediment export also depends on sediment availability, detachment, soil-surface condition, vegetation and residue cover, agricultural operations, and connectivity between sediment sources and the outlet. These temporal processes were represented only partly by the annual cover-management factor. When modelled hydrological inputs were used, errors were further amplified by the nonlinear MUSLE runoff-energy term.

The diagnostic five-regime formulation retained sediment-yield performance relatively close to that obtained with λ_{opt} -derived hydrological variables, whereas the diagnostic continuous reconstruction was weaker. This agrees with the strong preservation of runoff volume and peak discharge by $\lambda_{kmc,diag}$. Under predictive conditions, however, neither formulation reproduced event-scale sediment-yield variability satisfactorily. Peak-discharge errors contributed to this deterioration. The continuous formulation achieved slightly better efficiency and lower absolute bias than the predictor-assigned regimes, but both produced large event-level errors.

Similar fitted α values under global calibration and cross-validation suggest that performance loss was not primarily caused by coefficient instability. Nevertheless, calibrating α separately for each hydrological configuration allowed it to absorb systematic multiplicative differences. The comparison therefore assesses the preservation of inter-event sediment-yield variability after configuration-specific scaling rather than fully uncalibrated prediction.

Finally, sediment analysis was limited to 46 events with complete synchronized observations. Because this subset was determined by data availability and may underrepresent high-magnitude responses, the MUSLE results should not be assumed to characterize the complete upper tail of sediment export.

4.4. Scope, site specificity, and future development

The numerical results obtained in this study are specific to the monitored catchment, its climate, soils, topography, cropping systems, management history, observation period, and model parameterisation. The number of regimes, their centroids, frequencies, and hydro-meteorological characteristics should not be transferred directly to

other catchments or extrapolated to other regions. Even within comparable loess landscapes, different combinations of climate, soil condition, management, and drainage organization may produce different response structures.

The potentially transferable contribution of the study lies in the methodological framework rather than in the identified regime values. The framework separates three questions that are often confounded: whether recurrent runoff-initiation structure exists in observed responses, whether that structure can be inferred for new events, and how predictive uncertainty affects runoff volume, peak discharge, and sediment yield. Application elsewhere would require local model construction, calibration, and independent validation.

Future applications should prioritize more direct indicators of event-scale catchment state. Soil water content measured before events, or continuously simulated soil-water storage constrained by observations, may be more hydrologically relevant than fixed-window rainfall totals. These indicators could be combined with proxies of soil-surface condition, crop development, residue cover, tillage, crusting, and roughness.

Future developments should also consider routing structures that represent connected contributing areas, pathway activation, and distributed travel times as event-dependent components. This would shift connectivity from an effect partly absorbed by λ and the fixed lag towards a property represented within runoff generation and transfer. Additional complexity should be justified by out-of-sample gains in runoff, peak discharge, and sediment yield.

The framework should finally be tested across independent catchments and regions to determine whether recurrent runoff-response structures emerge under contrasting environmental and management conditions. Until such validation is available, the inferred regimes should primarily be regarded as site-specific diagnostic patterns rather than transferable hydrological classes or operational prediction rules.

5. Conclusion

This study showed that event-scale runoff initiation in the monitored agricultural loess catchment could not be represented adequately by a single fixed or published initial abstraction ratio. Five K-means regimes provided a stable and parsimonious diagnostic summary of the event-derived runoff responses, preserving both runoff volume and peak discharge effectively. However, the correct regime could not be assigned reliably to unseen events. The continuous linear formulation preserved less diagnostic information but produced more robust out-of-sample runoff-volume and peak-discharge predictions.

Diagnostic peak-discharge performance was substantial when event-derived abstraction information was available, particularly for λ_{opt} and the five-regime representation. Performance nevertheless declined markedly under out-of-sample prediction, highlighting the combined effects of runoff-initiation prediction errors and the simplified representation of spatially distributed, event-dependent runoff transfer through a single lag. Predictive sediment-yield performance was further reduced when predicted runoff and peak discharge were used as inputs to MUSLE.

The identified regimes and their numerical characteristics are specific to the monitored catchment and should not be extrapolated to other catchments or regions. The main contribution of the study is the framework used to distinguish diagnostic runoff-response structure, out-of-sample predictive performance, and the downstream effects of hydrological prediction errors within the modelling chain. Its application elsewhere will require local recalibration, additional catchment-state and connectivity information, improved routing, and independent validation.

CRedit authorship contribution statement

Pierre Baert: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation,

Conceptualization. **Matthieu Herpoel:** Writing – review & editing, Validation, Investigation. **Jeroen Meersmans:** Writing – review & editing, Methodology. **Charles Bièdiers:** Writing – review & editing, Validation, Methodology. **Aurore Degré:** Writing – review & editing, Supervision, Methodology, Funding acquisition.

Funding sources

This research was funded by the Service Public de Wallonie within the framework of the Intell'eau project (D65–1402).

Dataset link: <https://doi.org/10.58119/ULG/QPMNOU>

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.catena.2026.110497>.

References

- Alewell, C., Borrelli, P., Meusburger, K., Panagos, P., 2019. Using the USLE: chances, challenges and limitations. *International Soil and Water Conservation Research* 7 (3), 203–225. <https://doi.org/10.1016/j.iswcr.2019.05.004>.
- Aron, G., Lakatos, D.F., Miller, A.C., 1977. Infiltration formula based on SCS curve number. *J. Irrig. Drain. Div.* 103 (4), 419–427. <https://doi.org/10.1061/JRCEA4.0001169>.
- Baartman, J., Nunes, J., Masselink, R., Darboux, F., Bièdiers, C., Degré, A., Cantreul, V., Cerdan, O., Grangeon, T., Fiener, P., Wilken, F., Schindewolf, M., Wainwright, J., 2020. What do models tell us about water and sediment connectivity? *Geomorphology* 367. <https://doi.org/10.1016/j.geomorph.2020.107300>.
- Baltas, E.A., Dervos, N.A., Mimikou, M.A., 2007. Technical note: determination of the SCS initial abstraction ratio in an experimental watershed in Greece. *Hydrol. Earth Syst. Sci.* 11 (6), 1825–1829. <https://doi.org/10.5194/hess-11-1825-2007>.
- Boardman, J., Vandaele, K., Evans, R., Foster, I.D.L., 2019. Off-site impacts of soil erosion and runoff: why connectivity is more important than erosion rates. *Soil Use Manag.* 35 (2), 245–256. <https://doi.org/10.1111/sum.12496>.
- Bracken, L.J., Croke, J., 2007. The concept of hydrological connectivity and its contribution to understanding runoff-dominated geomorphic systems. *Hydrol. Process.* 21 (13), 1749–1763. <https://doi.org/10.1002/hyp.6313>.
- Bracken, L.J., Turnbull, L., Wainwright, J., Bogaart, P., 2015. Sediment connectivity: a framework for understanding sediment transfer at multiple scales. *Earth Surf. Process. Landf.* 40 (2), 177–188. <https://doi.org/10.1002/esp.3635>.
- Breiman, L., 2001. Random forests. *Mach. Learn.* 45, 5–32. <https://doi.org/10.1023/A:1010933404324>.
- Caletka, M., Šulc Michalková, M., Karásek, P., Fučík, P., 2020. Improvement of SCS-CN initial abstraction coefficient in the Czech Republic: a study of five catchments. *Water* 12 (7), 1964. <https://doi.org/10.3390/w12071964>.
- Costa, F.F. da, Paz, A.R. da, Picilli, D.G.A., 2019. Modified NRCS-CN-TUH methods for distributed rainfall-runoff modeling. *RBRH – Revista Brasileira de Recursos Hídricos* 24. <https://doi.org/10.1590/2318-0331.241920180104.e21>.
- Datry, T., Larned, S.T., Tockner, K., 2014. Intermittent rivers: a challenge for freshwater ecology. *BioScience* 64 (3), 229–235. <https://doi.org/10.1093/biosci/bit027>.
- de Vente, J., Poesen, J., Verstraeten, G., Govers, G., Vanmaercke, M., Van Rompaey, A., Arabkhedri, M., Boix-Fayos, C., 2013. Predicting soil erosion and sediment yield at regional scales: where do we stand? *Earth Sci. Rev.* 127, 16–29. <https://doi.org/10.1016/j.earscirev.2013.08.014>.
- Demarcin, P., Sohler, C., Mokadem, A.I., Dautrebande, S., Degré, A., 2011. Essai de cartographie des classes d'infiltrabilité des sols de Wallonie (Belgique). *Biotechnol. Agron. Soc. Environ.* 15 (1), 119–128.
- Evrard, O., Nord, G., Cerdan, O., Souchère, V., Le Bissonnais, Y., Bonté, P., 2010. Modelling the impact of land use change and rainfall seasonality on sediment export from an agricultural catchment of the northwestern European loess belt. *Agric. Ecosyst. Environ.* 138 (1–2), 83–94. <https://doi.org/10.1016/j.agee.2010.04.003>.
- Fu, S., Wang, N., Luo, L., 2011. Initial abstraction ratio in the SCS-CN method in the loess plateau of China. *Trans. ASABE* 54, 163–169. <https://doi.org/10.13031/2013.36271>.
- Gao, G.Y., Fu, B.J., Lü, Y.H., Liu, Y., Wang, S., Zhou, J., 2012. Coupling the modified SCS-CN and RUSLE models to simulate hydrological effects of restoring vegetation in the loess plateau of China. *Hydrol. Earth Syst. Sci.* 16, 2347–2364. <https://doi.org/10.5194/hess-16-2347-2012>.
- Hawkins, R.H., Woodward, D.E., 2019. Initial abstraction and curve numbers. *J. Hydrol. Eng.* 24 (6), 04019019. [https://doi.org/10.1061/\(ASCE\)HE.1943-5584.0001785](https://doi.org/10.1061/(ASCE)HE.1943-5584.0001785).

- Hawkins, R.H., Ward, T.J., Woodward, D.E., Van Mullem, J.A., 2008. Curve Number Hydrology: State of the Practice. American Society of Civil Engineers (ASCE), Reston, VA. <https://doi.org/10.1061/9780784410042>.
- Hrachowitz, M., Savenije, H.H.G., Blöschl, G., McDonnell, J.J., Sivapalan, M., Pomeroy, J.W., Cudennec, C., 2013. A decade of predictions in ungauged basins (PUB)—a review. *Hydrol. Sci. J.* 58 (6), 1198–1255. <https://doi.org/10.1080/02626667.2013.803183>.
- IRM-KMI, 2023. Climat de Chastre (INS 25117) – Normales climatologiques 1991–2020. Bruxelles, Belgique. https://www.meteo.be/resources/climatologie/climateCity/pdf/climate_INS25117_9120_fr.pdf.
- Jain, M.K., Mishra, S.K., Suresh Babu, P., Venugopal, K., Singh, V.P., 2006. Enhanced runoff curve number model incorporating storm duration and a nonlinear Ia-S relation. *J. Hydrol. Eng.* 11 (6), 631–635. [https://doi.org/10.1061/\(ASCE\)1084-0699\(2006\)11:6\(631\)](https://doi.org/10.1061/(ASCE)1084-0699(2006)11:6(631)).
- Kull, D.W., Feldman, A.D., 1998. Evolution of Clark's unit graph method to spatially distributed runoff. *J. Hydrol. Eng.* 3 (1), 9–19. [https://doi.org/10.1061/\(ASCE\)1084-0699\(1998\)3:1\(9\)](https://doi.org/10.1061/(ASCE)1084-0699(1998)3:1(9)).
- Laurant, A., Bollinne, A., 1976. L'érosivité des pluies à Uccle (Belgique). *Bull. Rech. Agron. Gembloux* 11, 149–173.
- MacQueen, J., 1967. Some methods for classification and analysis of multivariate observations. In: proceedings of the fifth Berkeley symposium on mathematical statistics and probability, Vol. 1: statistics, pp. 281–297. <https://projecteuclid.org/euclid.bsmsp/1200512992>.
- McGregor, K.C., Bingner, R.L., Bowie, A.J., Foster, G.R., 1995. Erosivity index values for northern Mississippi. *Transactions of the ASAE* 38 (4), 1039–1047. <https://doi.org/10.13031/2013.27921>.
- Michel, C., Andréassian, V., Perrin, C., 2005. Soil conservation service curve number method: how to mend a wrong soil moisture accounting procedure? *Water Resour. Res.* 41 (2). <https://doi.org/10.1029/2004WR003191>.
- Mirus, B.B., Loague, K., 2013. How runoff begins (and ends): characterizing hydrologic response at the catchment scale. *Water Resour. Res.* 49 (5), 2987–3006. <https://doi.org/10.1002/wrcr.20218>.
- Mishra, S.K., Singh, V.P., 2004. Validity and extension of the SCS-CN method for computing infiltration and rainfall-excess rates. *Hydrol. Process.* 18 (17), 3323–3345. <https://doi.org/10.1002/hyp.1223>.
- Mishra, S.K., Sahu, R.K., Eldho, T.I., Jain, M.K., 2006. An improved IaS relation incorporating antecedent moisture in SCS-CN methodology. *Water Resour. Manag.* 20 (5), 643–660. <https://doi.org/10.1007/s11269-005-9000-4>.
- Odongo, V.O., Onyando, J.O., Mutua, B.M., van Oel, P.R., Becht, R., 2013. Sensitivity analysis and calibration of the modified universal soil loss equation (MUSLE) for the upper Malewa catchment, Kenya. *International Journal of Sediment Research* 28 (3), 368–383. [https://doi.org/10.1016/S1001-6279\(13\)60047-5](https://doi.org/10.1016/S1001-6279(13)60047-5).
- Owens, P.N., 2020. Soil erosion and sediment dynamics in the Anthropocene. *Geomorphology* 366, 107222. <https://doi.org/10.1016/j.geomorph.2020.107222>.
- Panagos, P., Borrelli, P., Meusburger, K., van der Zanden, E.H., Poesen, J., Alewell, C., 2015. The new assessment of soil loss by water erosion in Europe. *Environ. Sci. Pol.* 54, 438–447. <https://doi.org/10.1016/j.envsci.2015.08.012>.
- Pineux, N., Colinet, G., Bièdiers, C.L., Degré, A., Legrain, X., 2017. Diachronic soil surveys to assess soil redistribution in loess-derived agricultural landscapes. *Geoderma Reg.* 10, 102–114. <https://doi.org/10.1016/j.geodrs.2017.06.001>.
- Poesen, J., Nachtergaele, J., Verstraeten, G., Valentin, C., 2003. Gully erosion and environmental change: importance and research needs. *Catena* 50 (2–4), 91–133. [https://doi.org/10.1016/S0341-8162\(02\)00143-1](https://doi.org/10.1016/S0341-8162(02)00143-1).
- Renard, K.G., Foster, G.R., Weesies, G.A., McCool, D.K. and Yoder, D.C. (1997). Predicting Soil Erosion by Water: A Guide to Conservation Planning with the Revised Universal Soil Loss Equation (RUSLE). Agriculture Handbook No. 703. Washington, DC: U.S. Department of Agriculture. ISBN 0-16-048938-5.
- Soil Conservation Service (SCS), 1972. National Engineering Handbook (NEH), Section 4: Hydrology. U.S. Department of Agriculture (USDA), Soil Conservation Service, Washington, DC.
- USDA-NRCS, 2004. Hydrologic soil-cover complexes. In: National Engineering Handbook, Title 210, Part 630, Chapter 9. <https://directives.nrcs.usda.gov/sites/default/files2/1712930634/Part%20630%20-%20Hydrology.pdf>.
- USDA-NRCS, 2021. Estimating runoff volume and peak discharge. In: National Engineering Handbook, Title 210, Part 650, Chapter 2, 2nd edition. Figure 2-7. <https://directives.nrcs.usda.gov/sites/default/files2/1712930818/31754.pdf>.
- Williams, J.R., 1972. Sediment-yield prediction with universal equation using runoff energy factor. In: present and prospective Technology for Predicting Sediment Yield and Sources (proceedings of the sediment-yield workshop, USDA sedimentation laboratory, Oxford, Mississippi), pp. 244–252. <https://ia600508.us.archive.org/32/items/presentprospecti40sedi/presentprospecti40sedi.pdf>.
- Williams, J.R., 1975. Sediment routing for agricultural watersheds. *Water Resour. Bull.* 11, 965–974. <https://doi.org/10.1111/j.1752-1688.1975.tb01817.x>.
- Wischmeier, W.H., 1959. A rainfall Erosion index for a universal soil-loss equation. *Soil Sci. Soc. Am. J.* 23, 246–249. <https://doi.org/10.2136/sssaj1959.03615995002300030027x>.
- Woodward, D.E., Hawkins, R.H., Jiang, R., Hjelmfelt, A.T., Van Mullem, J.A., Quan, Q. D., 2003. , Jr., Runoff curve number method: Examination of the initial abstraction ratio. In: World Water & Environmental Resources Congress 2003: 1–10. American Society of Civil Engineers. [https://doi.org/10.1061/40685\(2003\)308](https://doi.org/10.1061/40685(2003)308).