AGU PUBLICATIONS

Geophysical Research Letters

RESEARCH LETTER

10.1002/2016GL071480

Key Points:
- Soil loss response to runoff is strongly controlled by "geomorphic internal variability": microscale factors intrinsic to geomorphic system
- Predictive skill of deterministic soil loss models at event scale is likely to remain poor
- Erosion estimates must communicate uncertainty due to geomorphic external and internal types of variability

Supporting Information:
- Supporting Information S1

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Citation:
Kim, J., V. Y. Ivanov, and S. Fatichi (2016), Soil erosion assessment—Mind the gap, *Geophys. Res. Lett.*, *43*, 12,446–12,456, doi:10.1002/2016GL071480.

Received 15 JUN 2016
Accepted 15 DEC 2016
Accepted article online 17 DEC 2016
Published online 30 DEC 2016

Soil erosion assessment—Mind the gap

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Abstract Accurate assessment of erosion rates remains an elusive problem because soil loss is strongly nonunique with respect to the main drivers. In addressing the mechanistic causes of erosion responses, we discriminate between macroscale effects of external factors—long studied and referred to as "geomorphic external variability", and microscale effects, introduced as "geomorphic internal variability." The latter source of erosion variations represents the knowledge gap, an overlooked but vital element of geomorphic response, significantly impacting the low predictability skill of deterministic models at field-catchment scales. This is corroborated with experiments using a comprehensive physical model that dynamically updates the soil mass and particle composition. As complete knowledge of microscale conditions for arbitrary location and time is infeasible, we propose that new predictive frameworks of soil erosion should embed stochastic components in deterministic assessments of external and internal types of geomorphic variability.

1. Introduction

Quantifying the rates of overland soil erosion is essential for a range of problems, including the understanding of soil loss impacts on agricultural productivity, erosion-related sink of carbon, water quality due to nonpoint source pollutants, and flood control structure design [*Pimentel et al.*, 1995; *Syvitski et al.*, 2005; *Montgomery*, 2007; *Van Oost et al.*, 2007; *Quinton et al.*, 2010; *Chappell et al.*, 2015]. Economic costs of soil conservation have amounted to billions of dollars [*Pimentel et al.*, 1995; *Trimble and Crosson*, 2000; *Adhikari and Nadella*, 2011], and therefore, improvement of skill in soil loss prediction continues to be strongly desirable and has far reaching practical implications. While much research has shed light on crucial controlling factors, a complete understanding of process interdependencies across scales and therefore improvements of predictive capabilities have remained an elusive problem [*Trimble and Crosson*, 2000; *Montgomery*, 2007].

One of the essential challenges is that soil erosion is nonunique [*Kim and Ivanov*, 2014; *Kim et al.*, 2016b] for the same rainfall or runoff—the two primary forcings conventionally used to describe the erosion potential [*Selby*, 1993]. This is vividly demonstrated when data from adjacent plots undergoing the same experimental conditions are cross compared [*USDA*, 1965; *Boix-Fayos et al.*, 2006; *Kim et al.*, 2016a]: the nonuniqueness can exhibit up to 2 orders of magnitude difference [*Bagarello and Ferro*, 2004; *Boix-Fayos et al.*, 2007; *Nearing et al.*, 2007]. Erosion has been mostly attributed to the effects of *macroscale* (1) surface conditions such as soil and land use types, rock fraction, crop management, and conservation practices [*Harmel et al.*, 2007; *Sharmeen and Willgoose*, 2007; *Ward et al.*, 2009; *Garcia-Ruiz*, 2010; *Notebaerta et al.*, 2011; *Defersha and Melesse*, 2012; *Jomaa et al.*, 2013]; (2) site characteristics such as topography and slope [*Lane et al.*, 1997; *Phillips*, 2003; *Boix-Fayos et al.*, 2006; *Defersha et al.*, 2011]; and (3) rainfall properties such as intensity sequence, duration, and volume [*Edwards and Owens*, 1991; *González-Hidalgo et al.*, 2009; *Kim and Ivanov*, 2014]. Variability of soil loss caused by these *macroscale* factors will be referred to hereafter as "geomorphic external variability."

The influence of *microscale* conditions has also been indicated as a potential cause of variability in soil erosion [*Tisdall and Oades*, 1982; *Kwaad and Mucher*, 1994; *Bryan*, 2000; *Arnau-Rosalén et al.*, 2008; *Bussi et al.*, 2014] and was numerically investigated to illustrate how hysteresis loops in sediment transport arise [*Sander et al.*, 2011; *Zhong*, 2013] with a direct connection between the hysteretic phenomenon and the initial state of the surficial sediment layer and its evolution. We will refer to such microscale characteristics as "geomorphic internal variability." Specifically, the effect of (1) pedologic properties has been attributed to soil texture, aggregation, and shear strength [*Bryan*, 2000]. Among these, bulk soil texture can be reasonably assumed static, due to its slowly changing nature; its importance has been long recognized and is typically included in the geomorphic external variability [*Middleton*, 1930; *Bouyoucos*, 1935; *Knapen et al.*, 2007;

Gumiere et al., 2009]. The other pedologic properties—aggregation and shear strength—are much more variable in time and space, and their implications for erosion have remained largely unexplored [*Bryan*, 2000], likely due to limited capabilities to measure them. Additionally, one needs to recognize that microscale variations of (2) soil structure and degree of saturation lead to spatiotemporal variations of soil hydraulic properties and wetness conditions, thus inducing variability of the hydrologic partition (i.e., rainfall loss and runoff [*Noto et al.*, 2008]). Finally, variability of (3) surface roughness and surface elevation can result in contributions to geomorphic internal variability due to hydraulic effects. The random distribution of microscale topographic gradients and roughness elements can result in localized areas of flow acceleration and deceleration, with pronounced feedback regions (e.g., rill network development) [*Lei et al.*, 1998; *Simpson and Castelltort*, 2006; *Nord and Esteves*, 2010; *Papanicolaou et al.*, 2010; *Kim et al.*, 2012a; *McGuire et al.*, 2013]. Few laboratory and field experimental studies dealt with the issue of microscale variations in soil surface and subsurface conditions, and their inferences have remained case specific and difficult to generalize.

Variations of properties intrinsic to the system or caused by external factors have been recognized in various disciplines. They are referred to as "endogenous" and "exogenous" in geology, "autogenic" and "allogenic" in sedimentary geology, and "internal" and "external" in climate science. However, the meaning is different in each discipline (see Text S1 in the supporting information). Similarly, we introduce here the notions of geomorphic external and internal variability to unequivocally distinguish the impacts of macroscale external and microscale intrinsic factors on soil erosion. Furthermore, among the potential causes of internal variability we single out surface erodibility as, a priori, it may represent the dominant effect on erosion susceptibility [e.g., *Sidorchuk*, 2005]. The primary objective of this study is to demonstrate that these microscale spatiotemporal variations of soil erodibility are a fundamental source of internal variability at the scale of a single erosion event, with direct consequences for erosion predictability.

2. Data Analysis

To demonstrate the nonuniqueness and heavy-tailed frequency distributions of soil loss from upland areas, a comprehensive long-term data set, the one used to derive the Universal Soil Loss Equation (USLE, [*Wischmeier and Smith*, 1978]), is used. The USLE experimental design included monitoring replicated hillslopes with the same topography, soil type, rainfall and meteorological forcings, and land use conditions. The database integrated information from multiple locations and contains data on event-scale geomorphic and hydrologic variables such as storm characteristics, runoff, soil loss, and site-specific descriptions. USLE data are ideally suited to study the effects of microscale soil erodibility, given the replicated land surface and forcing conditions. The original data (1400 plot years) were filtered to ensure consistency required for plot-to-plot comparisons [*Kim et al.*, 2016a]. The resultant analysis data set includes 1218 plot years (102 individual plots) for 10 locations, totaling in 884 erosion events. The number of replicated plots for studied locations varies between 4 and 16. In this study, two representative locations, Clarinda, Iowa (312 events with 9 replicate plots, over 1932–1959), and Watkinsville, Georgia (213 events with 6 plots, over 1940–1960), are discussed in more detail due to their highest data availability. As we contend, however, the inferences are general and applicable to most hillslope-scale erosion assessments.

2.1. Geomorphic Variability

An interesting feature that emerges from the USLE data is the high nonuniqueness of geomorphic response for the same magnitude of event runoff (Figures 1a and 1b). While the high variability of soil loss is frequently observed in empirical data at various spatial scales [e.g., *Nearing et al.*, 2007], we note that Figures 1a and 1b show the *total* variability (referred to as the geomorphic total variability) because it is generated by many erosion events in *all* of the replicated plots. The spread of soil loss averaged over the replicate plots (Figures 1c and 1d) approximately refers to the variability that is external to the plot properties, i.e., what we have referred to above as the geomorphic external variability; numerous studies have addressed it in various detail. In contrast, Figures 1e and 1f show soil loss variations that are *intrinsic* to the soil system: identical plot-scale topographic characteristics, soil texture, land use, and rainfall/meteorologic forcing of replicated plots result in nearly identical runoff. The observed erosion differences in Figures 1e and 1f must be caused by variations in soil erodibility properties or some other *internal* properties of the system (such as pedologic, hydrologic, or hydraulic types of geomorphic internal variability, section 1). As clearly seen, soil erosion responses exhibit very high variability, reaching up to 2 orders of magnitude difference for the same forcing

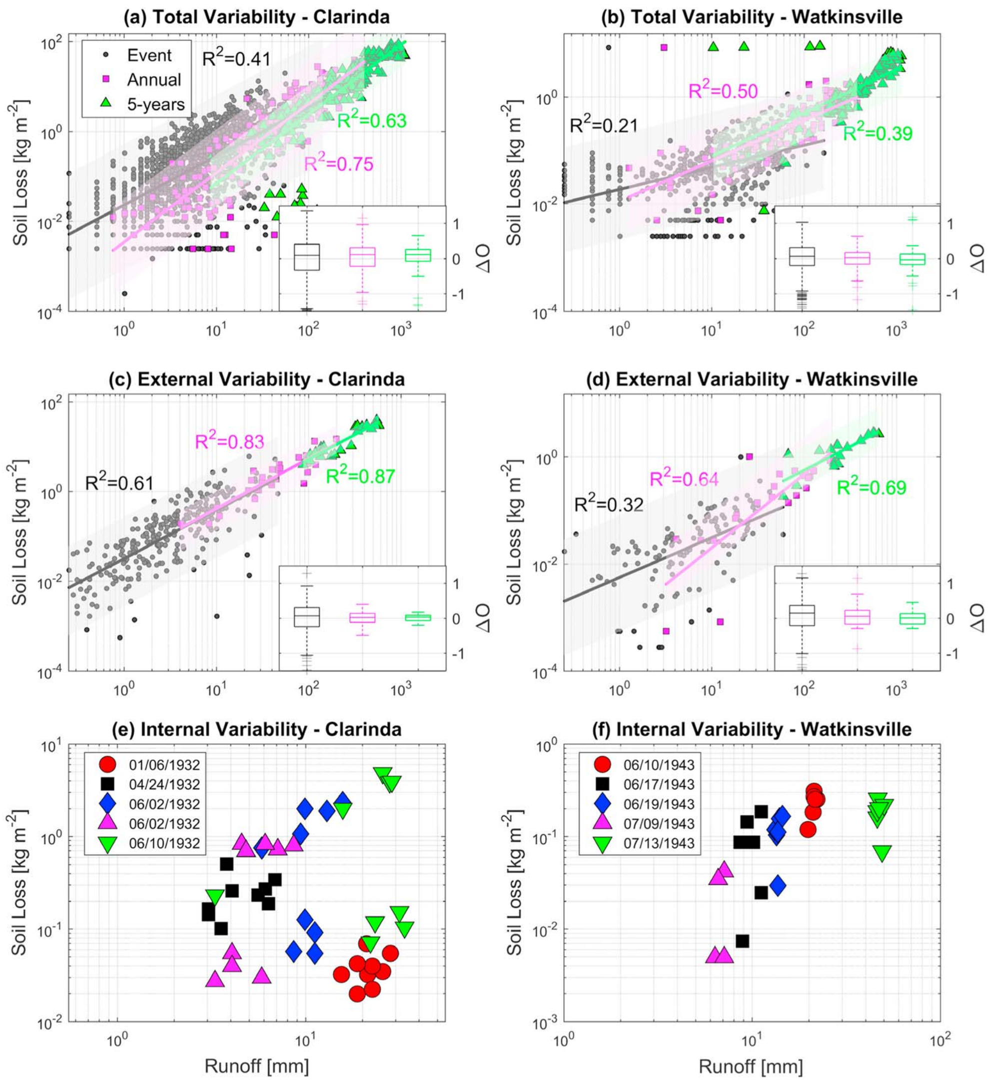

Figure 1. Measured soil loss versus runoff for the locations of Clarinda, Iowa (312 events with 9 replicate plots), and Watkinsville, Georgia (213 events with 6 plots). (a and b) Geomorphic total variability (all data from all replicate plots) and (c and d) geomorphic external variability (soil loss and runoff are averaged over the replicate plots). Several temporal scales are shown: event scale (black), annual (magenta), and 5 years (green). Boxplot inserts represent residuals from the regression line (thick lines) between runoff and soil loss, expressed as the order of magnitude difference (ΔO) computed for the three temporal scales (boxplots in Figures 1a and 1b are Figures 1d and 1j in *Kim et al.*, [2016a]). In each boxplot, the central mark is the median, the edges of the box are the 25th and 75th percentiles, and the upper and lower whiskers are the maximum and minimum, except for outliers ("plus" symbols) that are 1.5 times smaller or larger than the interquartile range from the 25th or 75th percentiles. The shaded areas in light grey, magenta, and green illustrate the order of magnitude differences corresponding to the upper and lower bounds in each boxplot, respectively. Calendar years are used to compute averages at the annual aggregation scale. To estimate 5 year values, a moving average is computed over each five consecutive calendar years (thus resulting in correlated 5 year averages). (e and f) Event-scale geomorphic internal variability illustrated for clarity for five selected rainfall-runoff events only. The selected events correspond to small coefficients of variation for runoff and illustrate the high variability of the corresponding soil loss.

(Figures 1e and 1f). Relevant processes that lead to microscale variations in soil surface conditions are due to the nonuniform supply of finer particles (weathering) [*Sharmeen and Willgoose*, 2006; *Cohen et al.*, 2010]; aggregate breakdown by trapped air (slaking); dryness of slaked clayey soil (sealing and crust formation); protection of the original soil layer by comparatively larger particles (shielding); chemical repelling interactions between cations (dispersion); and animal, plant, or human activities (bioturbation and management). These processes lead to soil surface erodibility, hydraulic properties, and spatial connectivity that are inevitably variable, space-time dependent, and ultimately unpredictable, providing the basis for why one cannot

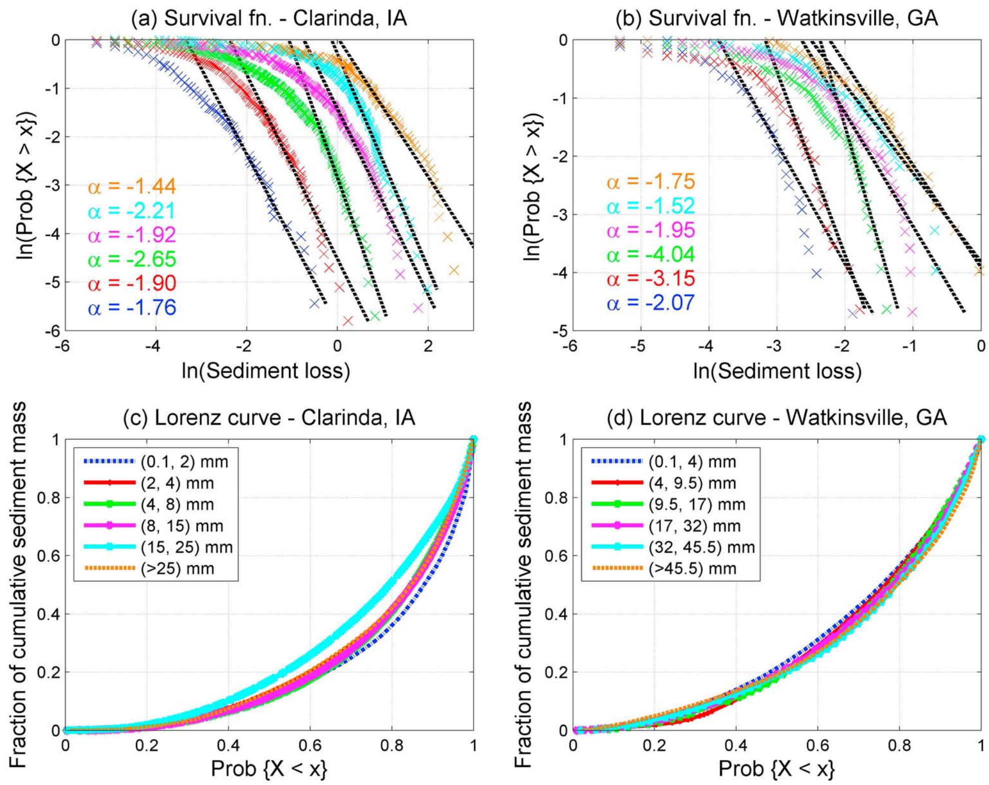

Figure 2. (a and b) Survival functions, Prob{$X > x$}. (c and d) Lorenz curves [*Lorenz*, 1905], computed from the conditional frequency distributions of soil loss corresponding to the binned ranges of surface runoff (in mm): the blue, red, green, magenta, cyan, and brown colors correspond to (0.1, 2), (2, 4), (4, 8), (8, 15), (15, 25), and (>25) for Clarinda, Iowa, and (0.1, 4), (4, 9.5), (9.5, 17), (17, 32), (32, 45.5), and (>45.5) for Watkinsville, Georgia. The variable "*X*" is event-scale sediment loss. The slopes in Figures 2a and 2b representing the Pareto index are computed using the approach of *Hill* [1975] based on the maximum likelihood method.

specify accurate initial conditions of soil particle distribution and spatial arrangements in deterministic erosion models.

2.2. Heavy-Tailed Distribution of Soil Loss

When inspected closely, the conditional frequency distributions of soil loss from the USLE database reveal heavy tails. This feature is apparent in the plots showing the power law behavior (Figures 2a and 2b). The larger (i.e., less negative) the slope of the tail (i.e., the Pareto index [*Hill*, 1975]), the heavier the tail of the distribution and thus the larger its departure from Gaussian. The corresponding Lorenz curves [*Lorenz*, 1905] (Figures 2c and 2d) show that the mass of the top 15–20% of soil loss events nearly equals the mass of the 80–85% smaller events. Such a heavy-tailed distribution is characteristic of systems where random anthropogenic, climatic, pedologic, hydrologic, and hydraulic perturbations constantly disrupt geomorphic state of the system, thereby moving it away from theoretical equilibrium [*Kim et al*., 2016a]. These perturbations are very common, and they therefore generate high variance of upland soil loss. As a result, erosion magnitudes much higher than the mean can occur at nonnegligible probabilities: more "frequently" than implied by the usual, implicit assumption of Gaussian variations, adopted in large-scale assessments (e.g., the National Resources Inventory, NRI) [*Nusser and Goebel*, 1997].

3. Modeling Analysis

One logical hypothesis from the analysis of empirical data at the event scale (Figures 1e and 1f), also adopted in other independently carried out pioneering studies of erosion variability [*Sander et al*., 2011; *Zhong*, 2013], is that for a given rainfall and runoff amount, the initial condition of soil substrate erodibility and its dynamic evolution exert a strong control on the *event-scale* geomorphic response. The possibility of large uncertainties in the characterization of geomorphic internal variability and thus low predictability power provides strong incentives for a systematic exploration of variations in hydrology-hydraulic-erosion-sediment transport processes. Below, we directly address the impact of uncertainty in geomorphic internal variability on soil loss at a unit-plot and runoff-event scales using a state-of-the-science two-dimensional model of overland flow and sediment transport, tRIBS-VEGGIE-FEaST [*Ivanov et al*., 2004, 2008; *Kim et al*., 2012b; *Kim et al*., 2013; *Kim and Ivanov*, 2015; *Kim et al*., 2016a] (see also Text S2).

3.1. Modeling Soil Surface Erodibility in Numerical Experiments

Recent studies demonstrated potential clues to how the initial and temporal evolution of geomorphic internal variability can impact soil loss [*Sander et al*., 2011; *Jomaa et al*., 2013; *Zhong*, 2013; *Kim and Ivanov*, 2014; *Kim et al*., 2016b]. Specifically, during a runoff event, rainfall and overland flow simultaneously drive erosion processes of detachment, entrainment, and deposition on original soil that is relatively intact and cohesive and in which contact forces bind the particles. Part of eroded materials is thus continuously redeposited over soil surface, and some fraction of redeposited materials is reeroded. These deposited, loose soil materials have higher erodibility than the original intact soil, with the difference reaching up to 2 orders of magnitude [*Proffitt et al*., 1991; *Jomaa et al*., 2010; *Heng et al*., 2011]. Further reentrainment and transport of deposited soil particles is thus promoted, leading to a complex intraevent and interevent temporal evolution of variations of surface erodibility. The deposited soil layer can exhibit two conflicting roles: it could both increase and decrease soil erosion of the subsequent event for the same magnitude and timing of overland flow according to the degree of shielding or exposure of fine loose material [*Sander et al*., 2011; *Zhong*, 2013; *Kim and Ivanov*, 2014; *Kim et al*., 2016a].

In order to represent the likely continuum of microscale surface erodibility characteristics and its variation among the replicate plots, we develop a large number of scenarios for the deposited (loose) soil mass in terms of its cover fraction and particle size distribution, with all other conditions remaining invariant. Specifically, we consider an exemplary location from the USLE database, Clarinda (Iowa), and an erosion event that took place on 31 July 1932 (chosen among 312 events as a representative event—yielding mean soil loss and runoff for that location, Figure S2). We use the USLE unit plot domain with 1.8 m (width), 22.1 m (length), and 1 m (depth). The scenarios of initial soil erodibility serve as input to tRIBS-VEGGIE-FEaST to address how the lack of knowledge on soil substrate composition and erodibility impacts the geomorphic response. Specifically, our approach considers multisize particle distributions of two soil surface types: the original, intact (cohesive) soil layer, and the deposited (noncohesive) soil layer, exhibiting different shear strengths [*Hairsine and Rose*, 1991; 1992]. The detachability in both layers is differentiated with two detachment parameters (equations (7) and (8) in *Kim et al*. [2013] and Table S1). The resistance to flow-driven entrainment in the original soil layer is accounted for with a parameter called the "specific energy of entrainment," while the resistance of the deposited layer to reentrainment is associated with the submerged weight of loose materials (equations (10) and (11) in *Kim et al*. [2013] and Table S1). One thousand random particle size distributions (PSDs) are generated to characterize the possible composition of the antecedent deposited layer (Figure 3a) for 10 magnitudes of its cover fraction (H). PSDs are obtained by the generation of combinations of six random numbers ranging from 0 to 1, satisfying the summation to 1. Thus, the corresponding total number of model simulations is 10,000 (e.g., $H = 0.1 \ldots 1$, Figures 3b and 3c) plus 1 ($H = 0$) representing intact soil. Other relevant details of the numerical setup are provided in *Kim et al*. [2016a]. In summary, the modeling design yields cases with exactly the same dynamics and amounts of infiltration, runoff, and surface flow, while the variability of soil initial conditions in the ensemble leads to differences in soil erosion. By using a number of particle sizes with different shear strengths (i.e., intact versus loose soil), the approach mimics the dynamics of soil properties by representing the degree, and cohesiveness of aggregations that are dynamically (temporally and spatially) updated within the model.

3.2. Model Results

The stochastic characterization of the initial condition with 10,001 soil substrates leads to the probability density function of soil loss that spans the variability of empirical observations for the nine replicate plots (Figure 3b). While the distribution extends to soil loss magnitudes (Figure 3b up to 1.373 kg m^{-2}) that are larger than the observed maximum, this simply conveys the theoretical plausibility of these responses with small probability that were not represented in the replicated plots (as well as, the potential effect of biases in model assumptions). The results of Figure 3b demonstrate that the initial condition of soil erodibility

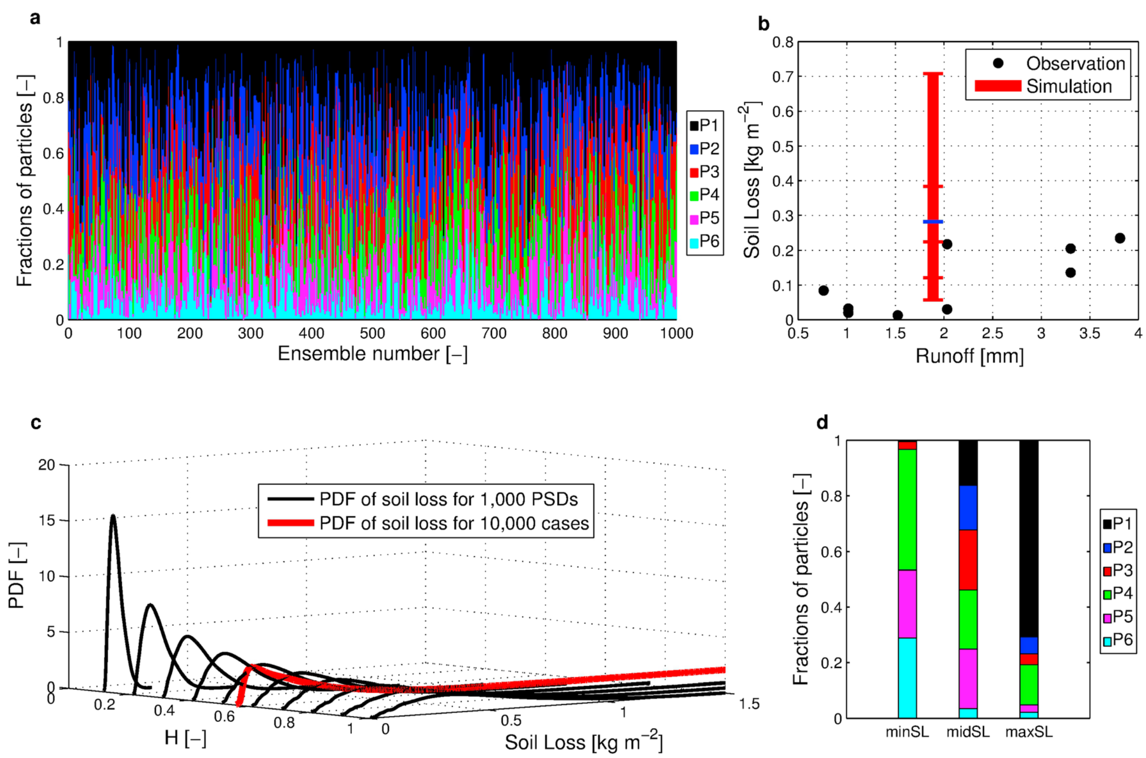

Figure 3. (a) A set of 1000 random particle size distributions (PSDs) characterizing the fractions of six particle size classes composing the antecedent deposited layer. (b) A comparison of soil loss and runoff data for 9 plots from the USLE database (black dots, erosion event on 31 July 1932) and the results of 10,001 simulations (red bar with horizontal lines representing the 5th, 25th, 50th, 75th, and 95th percentiles; the blue line represents the mean). (c) Empirical probability density functions (PDFs) representing 10,000 simulations of soil loss. The 10 PDFs (black line), each representing the results from 1000 ensemble members, correspond to varying conditions of the fraction of deposited soil material (H): from relatively intact ($H = 0.1$) to completely loose ($H = 1.0$) antecedent soil substrate. The overall PDF (red line) illustrates variation of soil loss for all simulation cases. (d) Particle compositions for three selected PSDs (marked as minSL, "midSL," and "maxSL") of antecedent deposited layer. The minSL and maxSL compositions correspond to the minimum and maximum amount of soil loss for each scenario of H fraction. The midSL has the same PSD as the original, intact soil layer.

strongly controls the magnitude of the geomorphic response. A narrower range of plausible yield magnitudes can be predicted only if soil surface conditions are better characterized. This is, however, unlikely and impractical; and therefore, the predictive skill of erosion models at the hillslope and event scale will likely remain severely handicapped.

To illustrate the relative importance of composition of antecedent deposited soil substrate on geomorphic response, a set of multiple linear regressions is developed using the 10,001 simulation cases to compute soil loss (SL) (Figure 3c): $\mathrm{SL} = \mathrm{SL}_0 + H{\cdot}\sum_{i=1}^{6} w_i f_i$ (kg m^{-2}) (see supporting information Text S3). The term SL_0 is the intercept for the case of a soil surface that is entirely "intact" (i.e., H is zero). The coefficients w_i represent weights for the fractions (f_i) of the six particle size classes. We find high sensitivity of soil loss to antecedent composition and that initially loose materials may not necessarily increase soil erosion. Specifically, for a fixed H, a higher fraction of loose, lighter materials on the soil surface intensifies soil erosion. A larger fraction of coarser, heavier particles can, however, result in a "shielding" layer (the negative signs of w, see supporting information) and thus inhibit erosion [*Kim and Ivanov*, 2014], when compared to the initially intact soil conditions. For example, the "minSL" PSD case in Figure 3d has the highest fractions of the three classes of coarser particles, and the regression equation yields a negative slope (-0.0106) of dependence on H. Positive slopes are characteristic of most other PSD cases.

For a given H, the large range of possible PSDs characterizing antecedent deposited soil material generates a positively skewed probability distribution of soil loss with a tail exhibiting a nearly exponential decay (Figure 3c). This response of nonuniqueness is entirely determined by the initial conditions of soil bed, since overland flow characteristics are identical [*Sander et al.*, 2011; *Zhong*, 2013; *Kim and Ivanov*, 2014]. As suggested above, the resultant variability in erosion response should be referred to as geomorphic internal variability, a more properly constrained reference than "natural variability" [*Nearing et al*., 1999] because the latter can include any kind of natural (e.g., including rainfall or radiation) external variability. A stochastic approach that accounts for the mass and distribution of materials of different erodibility characteristics (such as the two-bin conceptualization of intact and "loose" substrate types in Figure 3a) seems a suitable approximation to reflect the uncertainty of soil bed characteristics.

4. Discussion

4.1. Geomorphic Internal Variability and Soil Loss Assessments

The importance of spatiotemporal variations of microscale soil erodibility has been relatively ignored in erosion assessment studies, especially over large heterogeneous areas [*Kim et al*., 2016a]. One example is the approach used for monitoring of trends in erosion by the U.S. Department of Agriculture, which has contributed to the National Resources Inventory (NRI) [i.e., *Nusser and Goebel*, 1997]. Erosion monitoring is the result of statistically stratified spatial applications of a modeling tool, the Universal Soil Loss Equation (USLE) [*Wischmeier and Smith*, 1978], to assess the erosion potential at ~800,000 sample points throughout the United States [*Nusser and Goebel*, 1997]. Importantly, soil erosion rates computed in NRI for each sample point are based on time-invariant erosivity potential (rainfall) and erodibility (soil) factors, and the long-term assessment essentially consists of tracking changes of only site-specific parameters representing land use and management practices. In the context of research developed here, NRI (and most other contemporary erosion assessments [e.g., *Panagos et al*., 2014, 2015]) accounts for the variance of soil loss *among* unit areas (i.e., mostly the external variability), implicitly assuming that the variance *within* a unit area—the "sampling variance" attributed to the geomorphic internal variability here—is negligible. This research demonstrates that it is a misconception to equate the external variability to the total geomorphic variability since heterogeneities in particle size and erodibility characteristics of soil surfaces are always expected to be significant.

Furthermore, large-scale assessments (such as NRI or European Union-driven soil loss assessment) focus on the long-term soil loss averages that are perceived to be more relevant to policy makers or planners than the loss frequency distribution, reflecting our perception that with the average one "cannot be too far off" from the "likeliest expected." However, as seen in the USLE data, even at large temporal scales, there is distinct evidence of high variability of soil loss (e.g., Figure 1 and *Kim et al*. [2016a]) and long tail in the distribution cannot be discarded in certain problems of high relevance to policy making. This calls for a shift in erosion assessment paradigm, changing the focus from the first moment property to metrics characterizing distribution tails. The development of approaches that include stochastic principles to address key uncertainties will make policy-making process better informed.

4.2. Soil Loss as a Stochastic Problem From Deterministic Principles

It is infeasible (and impractical) to characterize varying soil surface conditions for any arbitrary location and time, implying low a priori predictability skill of many contemporary deterministic models. The development of stochastic principles that explicitly address quantification of uncertainty in erosion related to geomorphic internal variability is therefore essential. Methods that combine elements of deterministic and stochastic approaches can stem from solutions described in the literature [*Nearing*, 1991; *Wright and Webster*, 1991; *Lisle et al*., 1998; *Bryan*, 2000; *Sidorchuk*, 2009]. However, existing stochastic approaches, being derived in principle for erosion rates only, are still far from practical utility. Complete knowledge on the probability distribution of key stochastic variables (e.g., flow velocity, aggregate size, and soil cohesion within and between aggregates [*Sidorchuk*, 2005; 2009] or shear stress, and local soil resistance [*Nearing*, 1991]) is almost impossible to attain/parameterize from measurements in the real world. The approach used in this study is, however, flexible and can be applied to practical problems. This could be achieved by coupling physical hydraulic, hydrologic, and erosion and sediment transport models (e.g., tRIBS-VEGGIE-FEaST) to dynamically update soil properties (i.e., the amount, degree, and cohesiveness of aggregation) in time and space. Such an approach requires stochasticity in the definition of initial conditions and preserves the merits of mechanistic representation in computing the redistributions of flow and sediment.

4.3. Sources of Geomorphic Internal Variability

The sources of geomorphic internal variability have been conceptually attributed to microscale characteristics of pedologic, hydrologic, and hydraulic factors. Rather than directly accounting for all of them—an overly ambitious feat for a single study—we focus only on the spatiotemporal variations of soil erodibility, which are shown to lead to a level of soil loss variability commensurate with that of the event response of replicate experimental plots. Arguably, the ensuing implication is that geomorphic internal variability due to surface erodibility is a predominant factor determining envelopes of plot-, event-scale erosion response. While, a priori, this can be true for a range of other environmental settings, subsequent research should address the relative importance of all relevant sources of geomorphic internal variability. As is the case for uncertainty partition in other environmental sciences, the contributing components may result in nonadditive behavior [e.g., *Kim et al*., 2015; *Fatichi et al*., 2016], implying that only relative (i.e., with respect to each other) importance can be estimated. Nevertheless, such a step is necessary to decipher the role of individual factors that determine the internal variability.

4.4. Upscaling Variability

Scaling variability to larger spatial scales is extremely challenging as the USLE program did not accommodate geomorphic forms that exhibit spatial structure and connectivity, focusing solely on plots. No empirical data sets containing observations for *replicate catchments* are currently available. Nevertheless, sediment yield data for several smaller-scale watersheds located within a larger nesting basin [e.g., Figure 2 in *Nearing et al*., 2007] suggest high total variability. It is likely to be attributed to both the external (e.g., shrub versus grass cover condition) and internal variability, such as variations in surface forms that may include incised channels and rills, swales at different developmental stages, etc. The latter characteristics are conveyed at much smaller scales, as compared to the scale of the nesting watershed, and are not easy to address in watershed erosion studies. Therefore, they should be dealt with in the context of internal variability, and further studies should address scaling properties of geomorphic internal variability within contiguous hillslopes and watersheds.

5. Concluding Remarks

Despite the perceived importance and the high costs of soil conservation efforts, assessment of erosion rates remains a poorly constrained problem. Current large-scale erosion studies reflect a view that the integration over environmental conditions—i.e., accounting for geomorphic external variability only—yields estimates that are informative of the process. However, data from multiple environments demonstrate that soil loss is extremely variable and its frequency distributions exhibit heavy tails, implying that conventional assessments of soil loss focusing on central tendencies (and thus implicitly assuming Gaussian nature of variations) understate the true degree of predictive uncertainty.

Why is erosion loss estimation uncertain? This study contends that in addition to the commonly understood effect of geomorphic external variability (i.e., variations of rainfall properties, land use and management types, topography, soil texture, etc.), the response of multisized sediment to surface runoff events is strongly controlled by geomorphic internal variability, i.e., contributions from microscale variations in pedologic, hydrologic, and hydraulic processes. Space-time, dynamic variations of soil bed erodibility are emphasized as likely to be the most important [see also *Saletti et al*., 2015].

It is currently impossible to accurately assess the relative contributions of geomorphic internal and external variability as well as their partition through available empirical observations only. As precise knowledge of the associated internal processes will remain intangible, we have to accept that geomorphic predictive skill at the event scale is likely to remain poor, no matter how detailed erosion models will become in the future. The broader practical implication is that current practices of soil erosion assessment need to abandon not only the philosophy that entails symmetry of system behavior around "average"—central tendencies are plainly misinformative for physical systems driven by episodic, extreme inputs—but also the methodology that attributes the variance to a single source of factors.

To address the gap, we advocate the following endeavors in experimental and numerical studies. 1. Future long-term observations should be attained from as many replicated plots as possible to account for the geomorphic internal variability, as had already been emphasized in other studies [*Rüttimann et al*., 1995; *Nearing et al*., 1999]. Data from all previous research programs (e.g., the complete set of USLE observations) on rainfall, runoff, soil loss, and other vital supplementary measurements should be made available to scientists and practitioners. New types of monitoring, augmenting characterization of erosion process with data, for example, on microscale variability [e.g., *Hohenthal et al*., 2011] are also warranted 2. In terms of erosion models, new approaches that address the challenge of unavoidable uncertainties should be developed, and appropriate quantification of variability and tails of soil loss should become a standard practice 3. Confidence interval, risk, or other uncertainty measures need to accompany soil loss assessments. The development of methods that combine elements of deterministic and stochastic approaches, such as the one used in this study, or other approaches that attempt to partition the uncertainty related to geomorphic external and internal types of variability across various spatial scales should be pursued to develop a new predictive framework of soil erosion.

Acknowledgments
Data used in this analysis are available at www.umich.edu/~ivanov/HYDROWIT/Datashared/Data_Mind_the_Gap.zip. This study was supported by the National Science Foundation grant EAR 1151443 and by the Basic Science Research Program of the National Research Foundation of Korea funded by the Ministry of Education (2016R1D1A1B03931886). Any opinions, findings, and conclusions expressed in this material are those of the authors and do not necessarily reflect the views of the NSF. Authors are indebted to G. Sander and G. Willgoose for their thorough reviews and constructive criticism of this work.

References

Adhikari, B., and K. Nadella (2011), Ecological economics of soil erosion: a review of the current state of knowledge, in *Ecological Economics Reviews*, edited by R. Costanza, K. Limburg, and I. Kubiszewski, pp. 134–152 .

Arnau-Rosalén, E., A. Calvo-Cases, C. Boix-Fayos, H. Lavee, and P. Sarah (2008), Analysis of soil surface component patterns affecting runoff generation. An example of methods applied to Mediterranean hillslopes in Alicante (Spain), *Geomorphology*, *101*(4), 595–606.

Bagarello, V., and V. Ferro (2004), Plot-scale measurement of soil erosion at the experimental area of Sparacia (southern Italy), *Hydrol. Processes*, *18*(1), 141–157.

Boix-Fayos, C., M. Martínez-Mena, E. Arnau-Rosalén, A. Calvo-Cases, V. Castillo, and J. Albaladejo (2006), Measuring soil erosion by field plots: Understanding the sources of variation, *Earth Sci. Rev.*, *78*(3–4), 267–285.

Boix-Fayos, C., M. Martínez-Mena, A. Calvo-Cases, E. Arnau-Rosalén, J. Albaladejo, and V. Castillo (2007), Causes and underlying processes of measurement variability in field erosion plots in Mediterranean conditions, *Earth Surf. Processes Landforms*, *32*(1), 85–101.

Bouyoucos, G. J. (1935), The Clay Ratio as a Criterion of Susceptibility of Soils to Erosion, *Agron. J.*, *27*(9), 738–741.

Bryan, R. B. (2000), Soil erodibility and processes of water erosion on hillslope, *Geomorphology*, *32*(3-4), 385–415.

Bussi, G., F. Francés, J. J. Montoya, and P. Y. Julien (2014), Distributed sediment yield modelling: Importance of initial sediment conditions, *Environ. Modell. Software*, *58*, 58–70.

Chappell, A., J. Baldock, and J. Sanderman (2015), The global significance of omitting soil erosion from soil organic carbon cycling schemes, *Nature Clim. Change*, *6*, 187–191.

Cohen, S., G. Willgoose, and G. Hancock (2010), The mARM3D spatially distributed soil evolution model: Three-dimensional model framework and analysis of hillslope and landform responses, *J. Geophys. Res.*, *115*, F04013, doi:10.1029/2009JF001536.

Defersha, M. B., and A. M. Melesse (2012), Field-scale investigation of the effect of land use on sediment yield and runoff using runoff plot data and models in the Mara River basin, Kenya, *Catena*, *89*, 54–64.

Defersha, M. B., S. Quraishi, and A. Melesse (2011), The effect of slope steepness and antecedent moisture content on interrill erosion, runoff and sediment size distribution in the highlands of Ethiopia, *Hydrol. Earth Syst. Sci.*, *15*, 2367–2375.

Edwards, W. M., and L. B. Owens (1991), Large storm effects on total soil erosion, *J. Soil Water Conserv.*, *46*(1), 75–78.

Fatichi, S., Y. Y. Ivanov, A. Paschalis, N. Peleg, P. Molnar, S. Rimkus, J. Kim, P. Burlando, and E. Caporali (2016), Uncertainty partition challenges the predictability of vital details of climate change, *Earth's Future*, *4*, 240–251.

Garcia-Ruiz, J. M. (2010), The effects of land uses on soil erosion in Spain: A review, *Catena*, *81*(1), 1–11.

González-Hidalgo, J. C., M. de Luis, and R. J. Batalla (2009), Effects of the largest daily events on total soil erosion by rainwater. An analysis of the USLE database, *Earth Surf. Processes Landforms*, *34*(15), 2070–2077.

Gumiere, S. J., Y. Le Bissonnais, and D. Raclot (2009), Soil resistance to interrill erosion: Model parameterization and sensitivity, *Catena*, *77*(3), 274–284.

Hairsine, P. B., and C. W. Rose (1991), Rainfall detachment and deposition: Sediment transport in the absence of flow-driven processes, *Soil Sci. Soc. Am. J.*, *55*(2), 320–324.

Hairsine, P. B., and C. W. Rose (1992), Modeling water erosion due to overland flow using physical principles: 1. Sheet flow, *Water Resour. Res.*, *28*(1), 237–243, doi:10.1029/91WR02380.

Harmel, R. D., J. V. Bonta, and C. W. Richardson (2007), The original USDA-ARS experimental watersheds in Texas and Ohio: Contributions from the past and visions for the future, *Trans. Am. Soc. Agric. Biol. Eng.*, *50*(5), 1669–1675.

Heng, B. C. P., G. C. Sander, A. Armstrong, J. N. Quinton, J. H. Chandler, and C. F. Scott (2011), Modeling the dynamics of soil erosion and size-selective sediment transport over nonuniform topography in flume-scale experiments, *Water Resour. Res.*, *47*, doi:10.1029/2010WR009375.

Hill, B. (1975), A simple general approach to inference about the tail of a distribution, *Ann. Statistics*, *3*, 1163–1173.

Hohenthal, J., P. Alho, J. Hyyppä, and H. Hyyppä (2011), Laser scanning applications in fluvial studies, *Prog. Phys. Geogr.*, doi:10.1177/0309133311414605.

Ivanov, V. Y., R. L. Bras, and E. R. Vivoni (2008), Vegetation-hydrology dynamics in complex terrain of semiarid areas: 1. A mechanistic approach to modeling dynamic feedbacks, *Water Resour. Res.*, *44*, W03429, doi:10.1029/2006WR005588.

Ivanov, V. Y., E. R. Vivoni, R. L. Bras, and D. Entekhabi (2004), Catchment hydrologic response with a fully distributed triangulated irregular network model, *Water Resour. Res.*, *40*, W11102, doi:10.1029/2004WR003218.

Jomaa, S., D. A. Barry, B. C. P. Heng, A. Brovelli, G. C. Sander, and J. Y. Parlange (2013), Effect of antecedent conditions and fixed rock fragment coverage on soil erosion dynamics through multiple rainfall events, *J. Hydrol.*, *484*(0), 115–127.

Jomaa, S., D. A. Barry, A. Brovelli, G. C. Sander, J. Y. Parlange, B. C. P. Heng, and H. J. Tromp-van Meerveld (2010), Effect of raindrop splash and transversal width on soil erosion: Laboratory flume experiments and analysis with the Hairsine–Rose model, *J. Hydrol.*, *395*(1–2), 117–132.

Kim, J., and V. Y. Ivanov (2014), On the nonuniqueness of sediment yield at the catchment scale: The effects of soil antecedent conditions and surface shield, *Water Resour. Res.*, *50*, 1025–1045, doi:10.1002/2013WR014580.

Kim, J., and V. Y. Ivanov (2015), A holistic, multi-scale dynamic downscaling framework for climate impact assessments and challenges of addressing finer-scale watershed dynamics, *J. Hydrol.*, *522*(0), 645–660.

Kim, J., V. Y. Ivanov, and N. D. Katopodes (2012a), Hydraulic resistance to overland flow on surfaces with partially submerged vegetation, *Water Resour. Res.*, *48*, W10540, doi:10.1029/2012WR012047.

Kim, J., V. Y. Ivanov, and N. D. Katopodes (2013), Modeling erosion and sedimentation coupled with hydrological and overland flow processes at the watershed scale, *Water Resour. Res.*, *49*, 5134–5154, doi:10.1002/wrcr.20373.

Kim, J., V. Y. Ivanov, and S. Fatichi (2015), Climate change and uncertainty assessment over a hydroclimatic transect of Michigan, *Stochastic Environ. Res. Risk Assess.*, *30*, 923–944, doi:10.1007/s00477-015-1097-2.

Kim, J., V. Y. Ivanov, and S. Fatichi (2016a), Environmental stochasticity controls soil erosion variability, *Sci. Rep.*, *6*, 22065, doi:10.1038/srep22065.

Kim, J., A. Warnock, V. Y. Ivanov, and N. D. Katopodes (2012b), Coupled modeling of hydrologic and hydrodynamic processes including overland and channel flow, *Adv. Water Res.*, *37*, 104–126.

Kim, J., M. C. Dwelle, S. K. Kampf, S. Fatichi, and V. Y. Ivanov (2016b), On the non-uniqueness of the hydro-geomorphic responses in a zero-order catchment with respect to soil moisture, *Adv. Water Res.*, *92*, 73–89.

Knapen, A., J. Poesen, G. Govers, G. Gyssels, and J. Nachtergaele (2007), Resistance of soils to concentrated flow erosion: A review, *Earth Sci. Rev.*, *80*(1-2), 75–109.

Kwaad, F. J. P. M., and H. J. Mucher (1994), Degradation of soil structure by welding—A micromorphological study, *Catena*, *23*(3–4), 253–268.

Lane, L. J., M. Hernandez, and M. Nichols (1997), Processes controlling sediment yield from watersheds as functions of spatial scale, *Environ. Modell. Software*, *12*(4), 355–369.

Lei, T., M. A. Nearing, K. Haghighi, and V. F. Bralts (1998), Rill erosion and morphological evolution: A simulation model, *Water Resour. Res.*, *34*(11), 3157–3168, doi:10.1029/98WR02162.

Lisle, I. G., C. W. Rose, W. L. Hogarth, P. B. Hairsine, G. C. Sander, and J. Y. Parlange (1998), Stochastic sediment transport in soil erosion, *J. Hydrol.*, *204*(1–4), 217–230.

Lorenz, M. O. (1905), Methods of measuring the concentration of wealth, *Publications of the American Statisical Association*, *9*, 209–219.

McGuire, L. A., J. D. Pelletier, J. A. Gómez, and M. A. Nearing (2013), Controls on the spacing and geometry of rill networks on hillslopes: Rain splash detachment, initial hillslope roughness, and the competition between fluvial and colluvial transport, *J. Geophys. Res. Earth Surf.*, *118*, 241–256, doi:10.1002/jgrf.20028.

Middleton, H. E. (1930), Properties of soils which influence soil erosion., *U.S. Department Agriculture Technical Bulletin*, *178*.

Montgomery, D. R. (2007), Soil erosion and agricultural sustainability, *Proc. Natl. Acad. Sci. U.S.A.*, *104*(33), 13,268–13,272.

Nearing, M. A. (1991), A probabilistic model of soil detachment by shallow turbulent flow, *Transactions of the American Society of Agricultural Engineers*, *34*(1), 81–85.

Nearing, M. A., G. Govers, and L. D. Norton (1999), Variability in soil erosion data from replicated plots, *Soil Sci. Soc. Am. J.*, *63*(6), 1829–1835.

Nearing, M. A., M. H. Nichols, J. J. Stone, K. G. Renard, and J. R. Simanton (2007), Sediment yields from unit-source semiarid watersheds at Walnut Gulch, *Water Resour. Res.*, *43*, W06426, doi:10.1029/2006WR005692.

Nord, G., and M. Esteves (2010), The effect of soil type, meteorological forcing and slope gradient on the simulation of internal erosion processes at the local scale, *Hydrol. Processes*, *24*(13), 1766–1780.

Notebaerta, B., G. Verstraetena, P. Wardb, H. Renssenb, and A. V. Rompaey (2011), Modeling the sensitivity of sediment and water runoff dynamics to Holocene climate and land use changes at the catchment scale, *Geomorphology*, *126*(1-2), 18–31.

Noto, L. V., V. Y. Ivanov, R. L. Bras, and E. R. Vivoni (2008), Effects of initialization on response of a fully-distributed hydrologic model, *J. Hydrol.*, *352*(1-2), 107–125.

Nusser, S. M., and J. J. Goebel (1997), The National Resources Inventory: a long-term multi-resource monitoring programme, *Environmental and Ecological Statistics*, *4*, 181–204.

Panagos, P., K. Meusburger, C. Ballabio, P. Borrelli, and C. Alewell (2014), Soil erodibility in Europe: A high-resolution dataset based on LUCAS, *Sci. Total Environ.*, *479*, 189–200.

Panagos, P., P. Borrelli, J. Poesen, C. Ballabio, E. Lugato, K. Meusburger, L. Montanarella, and C. Alewell (2015), The new assessment of soil loss by water erosion in Europe, *Environ. Sci. Policy*, *54*, 438–447.

Papanicolaou, A. N., J. T. Sanford, D. C. Dermisis, and G. A. Mancilla (2010), A 1-D morphodynamic model for rill erosion, *Water Resour. Res.*, *46*, W09541, doi:10.1029/2009WR008486.

Phillips, J. (2003), Alluvial storage and the long-term stability of sediment yields, *Basin Res.*, *15*, 153–163.

Pimentel, D., et al. (1995), Environmental and economic costs of soil erosion and conservation benefits, *Science*, *267*(5201), 1117–1123.

Proffitt, A. P. B., C. W. Rose, and P. B. Hairsine (1991), Rainfall detachment and deposition: Experiments with low slopes and significant water depths, *Soil Sci. Soc. Am. J.*, *55*(2), 325–332.

Quinton, J. N., G. Govers, K. Van Oost, and R. D. Bardgett (2010), The impact of agricultural soil erosion on biogeochemical cycling, *Nat. Geosci.*, *3*(5), 311–314.

Rüttimann, M., D. Schaub, V. Prasuhn, and W. Rüegg (1995), Measurement of runoff and soil erosion on regularly cultivated fields in Switzerland—Some critical considerations, *Catena*, *25*(1–4), 127–139.

Saletti, M., P. Molnar, A. Zimmermann, M. A. Hassan, and M. Church (2015), Temporal variability and memory in sediment transport in an experimental step-pool channel, *Water Resour. Res.*, *51*, 9325–9337, doi:10.1002/2015WR016929.

Sander, G. C., T. Zheng, P. Heng, Y. Zhong, and D. A. Barry (2011), Sustainable soil and water resources: Modelling soil erosion and its impact on the environment, paper presented at Proceedings of MODSIM 2011, Modelling and Simulation Society of Australia and New Zealand Inc.

Selby, M. J. (1993), *Hillslope Materials and Processes*, Oxford Univ. Press, Oxford.

Sharmeen, S., and G. R. Willgoose (2006), The interaction between armouring and particle weathering for eroding landscapes, *Earth Surf. Processes Landforms*, *31*(10), 1195–1210.

Sharmeen, S., and G. R. Willgoose (2007), A one-dimensional model for simulating armouring and erosion on hillslopes: 2. Long term erosion and armouring predictions for two contrasting mine spoils, *Earth Surf. Processes Landforms*, *32*(10), 1437–1453.

Sidorchuk, A. (2005), Stochastic modelling of erosion and deposition in cohesive soils, *Hydrol. Processes*, *19*(7), 1399–1417.

Sidorchuk, A. (2009), A third generation erosion model: The combination of probabilistic and deterministic components, *Geomorphology*, *110*(1–2), 2–10.

Simpson, G., and S. Castelltort (2006), Coupled model of surface water flow, sediment transport and morphological evolution, *Comput. Geosci.*, *32*(10), 1600–1614.

Syvitski, J. P. M., C. J. Vörösmarty, A. J. Kettner, and P. Green (2005), Impact of humans on the flux of terrestrial sediment to the global coastal ocean, *Science*, *308*(5720), 376–380.

Tisdall, J. M., and J. M. Oades (1982), Organic matter and water-stable aggregates in soils, *J. Soil Sci.*, *33*(2), 141–163.

Trimble, S. W., and P. Crosson (2000), U.S. soil erosion rates: Myth and reality, *Science*, *289*(5477), 248–250.

USDA (1965), Predicting rainfall-erosion losses from cropland east of the rocky mountains: Guide for selection of practices for soil and water conservation, in *Agriculture Handbook*, vol. 282, U.S. Department of Agriculture, Washington, D. C.

Van Oost, K., et al. (2007), The impact of agricultural soil erosion on the global carbon cycle, *Science*, *318*(5850), 626–629.

Ward, P. J., R. T. V. Balen, G. Verstraeten, H. Renssen, and J. Vandenberghe (2009), The impact of land use and climate change on late Holocene and future suspended sediment yield of the Meuse catchment, *Geomorphology*, *103*(3), 389–400.

Wischmeier, W. H., and D. D. Smith (1978), *Predicting rainfall erosion losses: A guide to conservation planning*, USDA Agriculture Handbooks, Washington, D. C..

Wright, A. C., and R. Webster (1991), A stochastic distributed model of soil erosion by overland flow, *Earth Surf. Processes Landforms*, *16*(3), 207–226.

Zhong, Y. (2013), Modelling sediment transportation and overland flow PhD thesis, Univ. of Oxford.