

1 **Scale-dependent erosional patterns in steady and transient state landscapes**

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9

10 **Abstract**

11 Landscape topography is the expression of the dynamic equilibrium between external forcings (e.g.
12 climate and tectonics) and the underlying lithology. The magnitude and spatial arrangement of erosional
13 and depositional fluxes dictate the evolution of landforms during both statistical steady state (SS) and
14 transient states (TS) of major landscape reorganization. For SS landscapes, the common expectation is
15 that any point of the landscape has equal chance to erode at below or above the landscape median erosion
16 rate. We show here that this is not the case. Afforded by a unique experimental landscape that provided a
17 detailed space-time recording of erosional fluxes, and by defining the so-called “E50-area curve”, we
18 reveal for the first time that there exists a hierarchical pattern of erosion. Specifically, hillslopes and
19 fluvial channels erode more rapidly than the landscape median rate while intervening parts of the
20 landscape in terms of upstream contributing areas (colluvial regime) erode more slowly. We explain this
21 apparent paradox by documenting the dynamic nature of SS landscapes – landscape locations through
22 time may transition from being a hillslope to a valley and then to a fluvial channel due to ridge migration,
23 channel piracy and small-scale landscape dynamics. Under TS conditions caused by increased
24 precipitation, we show that the E50-area curve changes shape drastically during landscape reorganization.
25 Scale-dependent erosional patterns as observed in this study suggest benchmarks in evaluating numerical
26 models and interpreting the variability of sampled erosional rates in field landscapes.

27 **Introduction**

28 Landscape topography is sculpted via material fluxes that are controlled by the interplay of different
29 external forcings, such as climate and tectonics, with the underlying lithology (1-6). Landscapes
30 evolving under constant external forcings tend to achieve steady state (SS) configurations where the
31 material flux provided by rock uplift relative to baselevel is balanced by erosion. These landscapes can be
32 subdivided into different geomorphic process regimes, such as hillslopes, colluvial channels, and fluvial
33 channels, typically on the basis of variables such as topographic gradient and the upstream contributing
34 area that concentrates runoff (7). Whether the flux balance occurs across all of these regimes and at all
35 spatial scales (even pointwise), or is only applicable to the total or bulk fluxes at the landscape scale has
36 unavoidable consequences for the dynamic character of the landscape (8); the former situation leads to
37 time-invariant (frozen) landforms, while the latter allows for a dynamic component of SS landscapes.
38 While many numerical landscape evolution models result in *static* SS landscapes under simple boundary
39 conditions (usually vertical uplift and uniform rainfall) (9-14), physical experiments consistently produce
40 SS landscapes with dynamic landforms (15-18). This notion of dynamic SS landscapes, where drainage
41 divides continuously migrate and local erosion rates are therefore time-variant and spatially non-uniform,
42 is also supported by field and low-temperature thermochronological evidence (19-21). Dynamic
43 landscape behavior has been successfully incorporated into some numerical models by various
44 mechanisms such as landsliding (22), the use of more realistic flow-routing algorithms (23), or via
45 hillslope-fluvial process interactions (24).

46 If erosion rates vary in space and time, how can one distinguish steady state (SS) landscapes from
47 transient state (TS) landscapes, which respond to a change in external forcings? One approach would be
48 to compare the variability in erosion rates of SS landscapes, both in terms of their magnitudes and spatial
49 distribution, with those under TS conditions. Despite good knowledge of how individual landscape
50 components, such as alluvial rivers, bedrock rivers, or hillslopes (25-29), respond to change in external

51 forcing, our understanding of the organized erosional response of the landscape as a whole remains
52 elusive. Recent studies have tried to explain the variability of erosion rates in natural landscapes, due for
53 example to stochasticity of hillslope processes or knickpoint dynamics (21,30-32). However, a
54 comprehensive characterization of such variability, especially in terms of spatial patterns, would demand
55 repeated topographic data at high spatial resolution and over long periods of time. Such data are typically
56 not available for natural landscapes, making physical experiments (15-18,27,33,34) a necessary tool for
57 exploring erosion variability. While physical experiments have been used to document large-scale TS
58 landscape responses (15-18, 27), they have not typically been utilized to examine the multiscale spatial
59 variability of sediment fluxes within SS conditions to quantify the dynamic nature of SS landscapes and
60 to compare with TS responses.

61 In this paper, we analyze a unique experimental landscape, which provides a detailed space-time
62 record of the topography produced at the eXperimental Landscape Evolution (XLE) facility at St.
63 Anthony Falls Laboratory (17). We seek to (i) fully characterize SS landscapes in terms of local sediment
64 fluxes to advance our understanding of their dynamic nature, and (ii) quantify the manner in which
65 landscapes reorganize in response to changes in external forcing.

66

67 **Brief description of the experimental setup**

68 The eXperimental Landscape Evolution (XLE) facility (see Fig. 1 for schematic) consists of an
69 erosion box ($0.5 \times 0.5 \times 0.3 \text{ m}^3$) with two main controlling variables: (i) *uplift rate*, adjusted by lowering
70 two opposing sides mimicking mountain uplift, and (ii) *rainfall intensity*, simulated using 20 ultrafine
71 misting nozzles (droplet size $<10 \text{ }\mu\text{m}$) to achieve approximate spatial uniformity over the box. The
72 rainfall droplet size was small enough to avoid splash disturbances by the drop impact on the landscape
73 surface. The sediment used in the experiment was a homogeneous mixture of fine silica ($D_{50} = 25 \text{ }\mu\text{m}$)

74 with ~35% water content by volume. The facility was equipped with a high-resolution laser scanner that
 75 was able to obtain the topographic elevation $h(x,y,t)$ of the whole surface in 5 seconds at a spatial
 76 resolution of 0.5 mm and a vertical accuracy of better than 0.5 mm. For this experiment, topographic data
 77 were acquired every 5 minutes. We refer to *Singh et al.* (17) for a comprehensive discussion of the
 78 experimental setup and collected data.

79

80 **Steady State Landscape**

81 Assuming uniform grain size distribution and material porosity, as is the case in our experiment,

82 the pixel-wise measured topographic change $\left(\frac{\partial h_i}{\partial t}\right)$ relates to the flux divergence $\nabla \cdot \vec{q}_{s,i}$ and the

83 constant uplift rate U by the Exner equation:

$$84 \quad \frac{\partial h_i}{\partial t} = U - \nabla \cdot \vec{q}_{s,i} \quad (1)$$

85 The erosion depth (ED) at pixel i over a time interval $[t, t+\Delta t]$ is obtained by integrating the flux

86 divergence:

$$87 \quad ED_i(t, \Delta t) = \int_t^{t+\Delta t} \nabla \cdot \vec{q}_{s,i}(t) dt \quad (2)$$

88 where positive (negative) values of ED_i imply net erosion (deposition) at pixel i .

89 A landscape is said to be at SS when the erosional fluxes balance out the sediment flux provided
 90 by the rock uplift. Depending on the scale at which this flux balance is applicable, two different types of
 91 SS can be defined (8). In *flux* SS, the total flux of sediment leaving the system balances the amount
 92 provided by tectonic uplift during an interval of time Δt :

93
$$\text{SS: } \langle ED_i^{SS}(t, \Delta t) \rangle = \langle ED_i^{SS}(\Delta t) \rangle = U \cdot \Delta t \quad (3)$$

94 where $\langle \cdot \rangle$ denotes spatial average over all pixels i and the first equality acknowledges the time-
 95 independent average flux. Flux SS is also referred as *statistical SS*, acknowledging that several statistical
 96 properties of the landscape such as slope and upstream contributing area probability distributions,
 97 sediment discharge or river network properties, remain constant (17,18). In *topographic SS*, the surface
 98 elevation does not change over time because the divergence of sediment flux is the same at every point of
 99 the landscape and is exactly equal to the uplift rate:

100
$$\frac{\partial h_i}{\partial t} = 0; \quad U = \nabla \cdot \bar{q}_{s,i} \quad \forall i \quad (4)$$

101 Using the XLE facility, we let the landscape evolve to a statistical SS with constant uplift rate U
 102 = 20 mm/h and constant precipitation rate $P = 45$ mm/h for 8 hours. SS conditions were inferred by a
 103 time-invariant sediment flux rate equal to the uplift rate (17). Fig. 2 illustrates the SS nature of the
 104 landscape by showing the time invariance of two important statistical properties: the slope-area curve
 105 (Fig. 2A), and the probability distribution of pixel-wise erosion depths, which also confirms a constant
 106 mean erosion depth (Fig. 2B). The slope-area curves were obtained from four consecutive topographies
 107 at SS (measured 5 min apart) using the steepest downslope direction to estimate local slope and the D-
 108 infinity algorithm (36,37) to compute upstream contributing areas. Slope-area curves are a useful tool to
 109 reveal the scales of geomorphic organization (7,38-45). From changes in the trends of these curves we
 110 can differentiate three process regimes: hillslopes, draining upstream contributing areas that range from 1
 111 to approximately 10 pixels, or up to 2.5 mm²; a colluvial regime corresponding to intermediate upstream
 112 contributing areas of 2.5 to 250 mm²; and a fluvial regime corresponding to upstream contributing areas
 113 larger than 250 mm². The specific values are obtained via analysis of slope increments and detection of
 114 change of trends as discussed in *Singh et al.* (17). The overlap of consecutive slope-area curves derived
 115 from different topographies at SS shows that there was no significant change in these regimes and thus no

116 structural reorganization of the landscape. Notice that the higher variability observed for large upstream
117 contributing areas is due to the smaller sample size available to compute the corresponding slope. We also
118 computed probability density functions (PDFs) of the pixel-wise erosion depth, with positive values
119 indicating erosion and negative values deposition, computed by taking differences of elevation of
120 consecutive topographies measured 5 min apart. From the overlapping distributions and from the results
121 of a Kruskal-Wallis test (46), we conclude that the PDFs are statistically indistinguishable, revealing the
122 statistical SS nature of erosional and depositional processes. We also note that the shape of the PDFs
123 reveals that the landscape is not frozen (that is, it is not a topographic SS); if it were, the PDF would be
124 just a Dirac delta function (single value) centered at the value of the uplift depth ($U \cdot \Delta t$ - i.e. depth of
125 material provided by the uplift in $\Delta t = 5$ min). The observed complex distribution of local erosion depths
126 raises the question about the spatial distribution of the variability in the erosion magnitude. In the next
127 section we unveil, via a spatial analysis of the sediment fluxes, a stationary *scale*-dependent pattern of
128 erosion for SS landscapes.

129

130 ***Scale-dependent (or hierarchical) erosional patterns: the E50-area curve***

131 We ask whether there exists a characteristic erosional signature of steady state landscapes
132 reflective of their geomorphologic organization. For that we interrogate the landscape in terms of the
133 pixel-wise erosion (deposition) depth as a function of the pixel location parameterized by the upstream
134 contributing area. Specifically, we compute the probability density function of erosion depth for sets of
135 pixels grouped in 100 equal probability area bins according to their upstream drainage area A_i . We
136 summarize the results of this analysis in a so-called “E50-area curve” (Fig. 3A), where we estimate the
137 probability that the pixel-wise erosion depth within each drainage area bin exceeds the median erosion
138 depth of the whole landscape. We highlight two main points revealed by the E50-area curves. First, the
139 stationary shape of the curve for fluxes computed at different SS intervals reveals a statistical pattern that
140 is persistent over time; that is, the E50-area curve is a statistical signature of the steady state landscape.

141 Second, the curves have a characteristic non-linear shape that deviates from the trivial horizontal curve
142 (equal to 0.5 for all values of upstream contributing area) that would be expected under topographic SS.
143 Specifically, the E50-area curve reveals that the regimes of the landscapes characterized by both small
144 (hillslopes) and large (fluvial) contributing areas erode significantly more than the median of the
145 landscape.

146 It can seem paradoxical to argue that SS landscapes possess a time invariant erosional signature
147 that is non-uniform across different scales, where for instance hillslopes are consistently more likely to
148 erode than the rest of the landscape. This erosional pattern also apparently contradicts the possibility of
149 maintaining the statistical properties of a steady state landscape, such as invariant total relief or stationary
150 slope-area curves. The missing factor needed to reconcile these ostensible discrepancies is the dynamic
151 character of the landforms at SS. Asserting that hillslopes are more likely to erode is not equivalent to
152 saying that fixed locations in the landscape are more likely to erode, because individual pixels can evolve
153 and belong to different geomorphic regimes at different times. A higher erosion rate in the hillslope
154 pixels reduces their elevation over time and hence changes the upstream contributing areas, eventually
155 shifting them into a regime with a lower erosion rate. To illustrate this dynamic nature of the SS
156 topography, Fig. 3B shows that 40% of the hillslope pixels (i.e., pixels with upstream contributing areas
157 of less than 0.5 mm^2) drain larger areas after five minutes of landscape evolution under SS (see Fig. S1
158 for alternative values of initial upstream area). This dynamic behavior ensures that erosion rates estimated
159 using sediment fluxes measured at a fixed location over sufficiently long periods will converge to the
160 erosion rate of the whole landscape, as that fixed location *visits* different regimes of the E50-area curve.

161 We emphasize that patterns in erosional fluxes, as shown by the E50-area curve, are easily
162 disguised by examining the landscape in a different manner, e.g., by random sampling. For example, Fig.
163 3C shows the probability of erosion for pixels contained in random samples of the same size as those used
164 to build the E50-area curve. The stationarity of the probabilities over time for fixed locations is additional
165 evidence supporting the steady state of the landscape, and by itself might lead one to conclude that no

166 persistent spatial patterns of erosion are expected once steady state is reached. Figure S2 shows the
167 estimation of erosional rates when different spatial extents are considered depicting a robust behavior of
168 those estimators for sample sizes even smaller than the one used in Fig. 3C.

169 The existence of time-invariant spatially-explicit patterns of erosion in SS landscapes opens
170 questions of how to detect and characterize the response of the landscape to changing external forcing. In
171 the next section, we show that a similar analysis reveals a significantly distinct hierarchical response of a
172 landscape under increased rainfall intensity.

173

174 **Transient State Landscape**

175 A transient state (TS) landscape can be defined as a landscape with non-zero net material flux at
176 the landscape scale. A TS is normally a consequence of abrupt changes in the external forcings that drive
177 landscape evolution, such as rock uplift rate and precipitation. Using our experimental facility, we
178 investigate the landscape reorganization at the onset of the TS that is produced by a five-fold increase in
179 rainfall intensity. Under these conditions (*i.e.*, increasing rainfall intensity), the amount of sediment
180 leaving the system significantly exceeds the sediment production provided by tectonic uplift:

$$181 \quad \text{TS: } \langle ED_i^{TS}(t, \Delta t) \rangle > U \cdot \Delta t \quad (5)$$

182 Note that ED_i^{TS} depends on both t and Δt ; the disequilibrium expressed in Eq. 5 gradually decays with
183 time (17) as the landscape approaches a new SS.

184 We are interested in comparing the distinct dynamic response of the reorganizing landscape
185 during the onset of TS conditions with the inherent spatial variability in erosion rates within the SS
186 landscape. For a meaningful comparison of the sediment fluxes, however, the two landscapes must first
187 be rendered comparable in terms of the total volume of sediment that is removed. For this, we integrate

188 the SS and TS landscapes over different time intervals, i.e. over a longer time interval ($k\Delta t$) at SS to
 189 match the eroded sediment volume produced over an interval Δt under increased precipitation at TS:

$$190 \quad \langle ED_i^{SS}(k\Delta t) \rangle = \langle ED_i^{TS}(t, \Delta t) \rangle \quad (6)$$

191 Acknowledging the SS condition of Eq. 3, the time-rescaling factor k , which depends on both t and Δt ,
 192 can be estimated by the volume rescaling factor, i.e., as $k = \langle ED_i^{TS}(t, \Delta t) \rangle / \langle ED_i^{SS}(\Delta t) \rangle$. Focusing our
 193 analysis on the first five minutes (i.e., $\Delta t = 5$ mins) after the transition to increased precipitation rate, we
 194 found $k = 2.6$, meaning that an integration time of 13 mins (2.6×5 mins) is needed at SS to dislodge the
 195 same total volume of sediment as the first 5 minutes under TS. This ratio decreases as the integration time
 196 increases and eventually approaches $k=1$ at a new SS (since the uplift rate remains the same). During the
 197 experimental run, landscape topography was acquired every five minutes, and so we can only scale the SS
 198 landscape by integer values of k . By comparing the PDFs of erosion depths corresponding to different
 199 values of k (see Fig. S3), we select $k=2$ (i.e., topographies measured 10 min apart) in the rest of the study
 200 as the best estimate within the available temporal discretization.

201 The spatial patterns of erosion at TS are substantially different from those at SS (Fig. 4). To
 202 quantify the distinct distributed response occurring during the onset of the TS, we show in Fig. 5A the
 203 E50-area curves for SS ($\Delta t = 10$ mins) and for the onset of the TS ($\Delta t = 5$ mins), as well as the slope-area
 204 curve corresponding to the SS. Importantly, the E50-area curve at TS shows a significant deviation from
 205 that at SS within three distinct regions of erosional regime change under increased precipitation: (i) for
 206 areas $A_i < 0.75 \text{ mm}^2$, there is a large percentage of high-erosion pixels for both SS and TS, but erosion is
 207 enhanced during TS compared to SS; (ii) for areas $0.75 \text{ mm}^2 < A_i < 50 \text{ mm}^2$, the percentage of high-
 208 erosion pixels decreases with upstream drainage area in both SS and TS, but the rate of decrease is larger
 209 in TS than SS; (iii) for areas $A_i > 50 \text{ mm}^2$, there is a regime shift from downstream-increasing to
 210 downstream-decreasing erosion: erosion increases sharply with A for SS, but for TS the fraction of highly

211 eroding pixels decreases with A. Putting these results in the geomorphic context provided by the slope-
212 area curve, we can conclude that during landscape reorganization in TS, hillslopes undergo accelerated
213 erosion, colluvial and slightly convergent regions experience reduced erosion, and fluvial channels
214 experience a reduction of their channel incision rate (erosion) due to the increase of sediment flux
215 delivered from upstream. These results are compatible with numerical simulations by *Tucker and*
216 *Slingerland* (10). It is important to note as well that the emergent scales that demarcate these erosional
217 regime transitions coincide fairly well with the scales of geomorphic process regime transitions from
218 hillslope to colluvial to fluvial obtained from the slope-area curve (38,44), as illustrated in Fig. 5A. To
219 the best of our knowledge, this is the first time that such erosional regime transitions (revealed by the
220 E50-area curves) and geomorphic process regime transitions (revealed by the slope-area curves) have
221 been explored simultaneously at the landscape scale to detect and interpret reorganization.

222 This reorganization can be visualized by explicitly positioning on the landscape all pixels that
223 transition from high to low erosion and vice versa during reorganization, relative to the landscape median
224 erosion rate. Fig. 5B-D depicts a single drainage basin and shows the parts of the landscape that have
225 changed their erosional behavior during the onset of TS. It is seen that hillslope pixels are the first to
226 respond to the increased precipitation rate, shifting from low to high erosion values (Fig. 5C). In contrast,
227 fluvial channels shift from high to low erosion values, so that incision rates are reduced due to accelerated
228 upstream erosion and sediment supply (Fig. 5D). Although there is no distinction between sediment and
229 bedrock in our experiment, these results resonate with recent models that suggest that sediment fluxes can
230 exert a significant control in the river incision rates (47-50). The top-down reorganization of the
231 landscape, with information flowing from hillslopes to channels, is distinct to the commonly-held view of
232 landscape reorganization in response to base level changes, in which channels lead and hillslopes follow
233 (48,51-54).

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235

236 **Concluding Remarks**

237 The question of whether a steady state (SS) landscape achieves a frozen topography that exhibits
238 no variability in local erosion rates at any scale, or achieves a statistical equilibrium within which erosion
239 dynamically and preferentially changes locally while maintaining the large-scale balance of fluxes,
240 remains open. Here, we analyzed a densely monitored experimental landscape to present evidence that
241 SS is characterized by a hierarchical pattern of erosion summarized in a new curve called the E50-area
242 curve. This curve quantifies the probability of a location eroding above or below the landscape median as
243 a function of the location's upstream contributing area. We explained this curve in terms of the internal
244 dynamics of the SS landscape by showing that locations of the landscape switch geomorphic regimes
245 through time (e.g., hillslopes erode more than the landscape median, lowering their relative elevation and
246 increasing their upstream contributing area, thus shifting to a new geomorphic regime). We proposed that
247 the E50-area curve is a characteristic signature of SS landscapes that should be reproduced in numerical
248 models. Finally, we showed how the shape of the E50-area curve changes when the landscape is in a
249 transient state (TS) in response to a change in external forcing. How the shape of the E50-area curve
250 evolves as the landscape approaches a new equilibrium in response to its forcing, and whether this new
251 equilibrium differs from the original one, are open questions currently under experimental and analytical
252 investigation. Extended experimental data will also allow investigation of the variability of the E50-area
253 curve under different external forcings as an emergent property of landscape organization, informing
254 numerical landscape evolution models and providing important information for quantifying the
255 uncertainty of sampled erosional rates in field landscapes.

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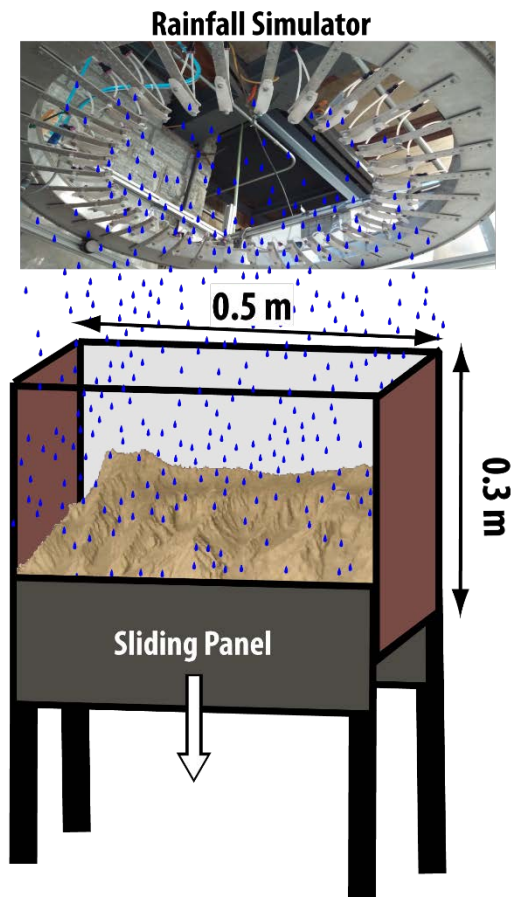
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Fig. 1. Schematic representation of the eXperimental Landscape Evolution (XLE) facility at the St. Anthony Falls Laboratory, University of Minnesota.

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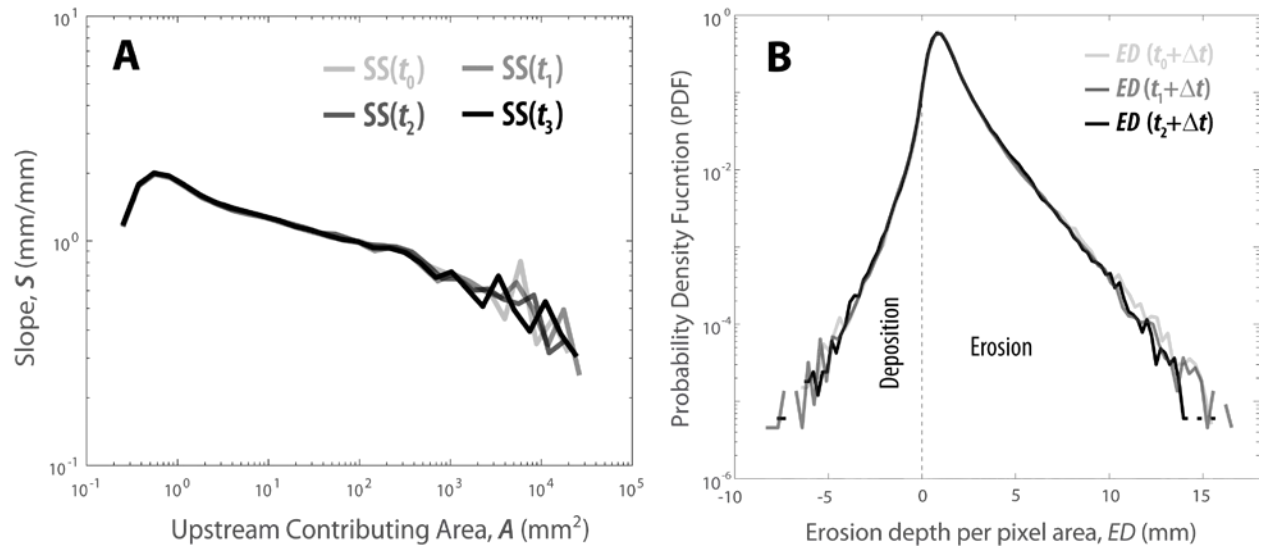
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449 **Fig. 2. Characterization of statistical steady state (SS) landscapes.** (A) Slope-area curves of
 450 the landscape at SS computed for four different instances, separated by 5 min intervals. Note that
 451 the curves show averages over logarithmic area bins. (B) Probability density functions (PDFs) of
 452 the pixel-wise erosion depths computed by differencing the topographic data of the SS landscape
 453 at consecutive (5 min apart) instances. The shape of the PDF confirms the statistical nature of
 454 the SS landscape (a frozen landscape would have a Dirac delta PDF centered at the uplift depth
 455 corresponding to 5 min). The question we pose is whether every pixel of the SS landscape has
 456 equal likelihood to experience any value of this PDF (equal chance of experiencing above or
 457 below the landscape median erosion) as commonly assumed. We show that this is not the case
 458 and indeed there is a preferential scale-dependent organization of erosional fluxes as shown in
 459 Fig. 3.

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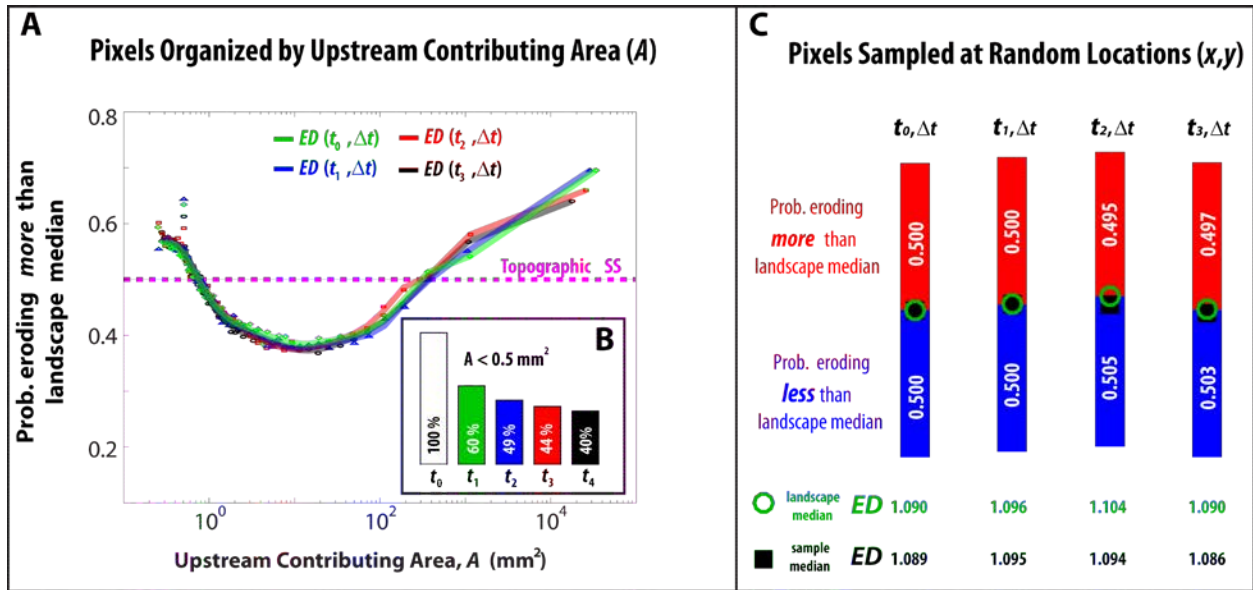
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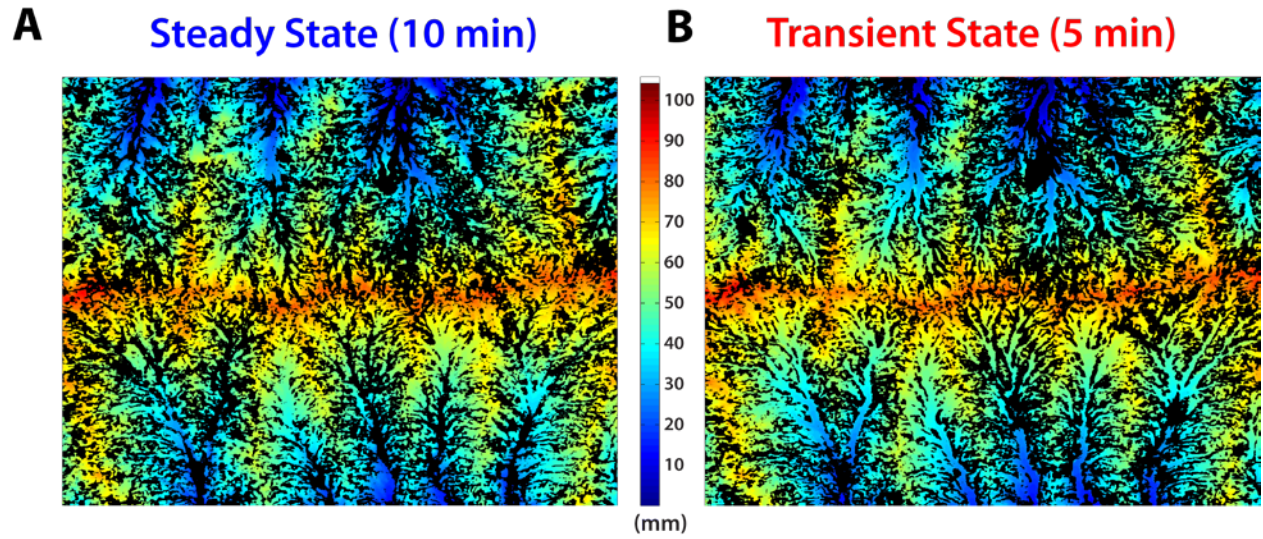
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469 **Fig. 3. Scale-dependent steady state landscape.** (A) *E50-area curves*: The four curves (green, blue,
 470 red and black) correspond to the fraction of pixels that erode more than the landscape median plotted
 471 against upstream contributing area, A , and are estimated using five consecutive (5 min apart) topographies
 472 at steady state. The four curves overlap with each other, revealing a stationary statistical signature of the
 473 erosional processes acting on the landscape. The shape of E50-area curves for SS topographies clearly
 474 differs from the straight line at 0.5 probability, which would be expected either for a strict topographic
 475 (frozen) steady state landscape, or for the case where the likelihood of experiencing any value of the PDF
 476 of erosion depths is the same across the landscape. (B) *Dynamic landforms at SS*: The nonlinear shape of
 477 the E50-area curve shows the dynamic nature of the landforms. To illustrate the degree of their dynamic
 478 behavior, we identify at a given time (t_0) the location of all the pixels on the landscape characterized by A
 479 $< 0.5 \text{ mm}^2$ (100%). For subsequent topographies acquired 5 min apart, we compute the percentage of
 480 those locations, which are still characterized by A in the same interval ($A < 0.5 \text{ mm}^2$). A similar analysis
 481 for different values of A is shown in Fig. S1. (C) *Random locations*: For a sample consisting of 1% of the
 482 landscape extent chosen randomly across the spatial domain, we examine the fraction of pixels within the
 483 sample that erode more and less than the median of the landscape over subsequent topographies. This
 484 figure evidences how the pattern revealed by the E50-area curve can be easily dismissed when spatial
 485 erosional depth patterns are interrogated in a different manner (e.g., random sampling).

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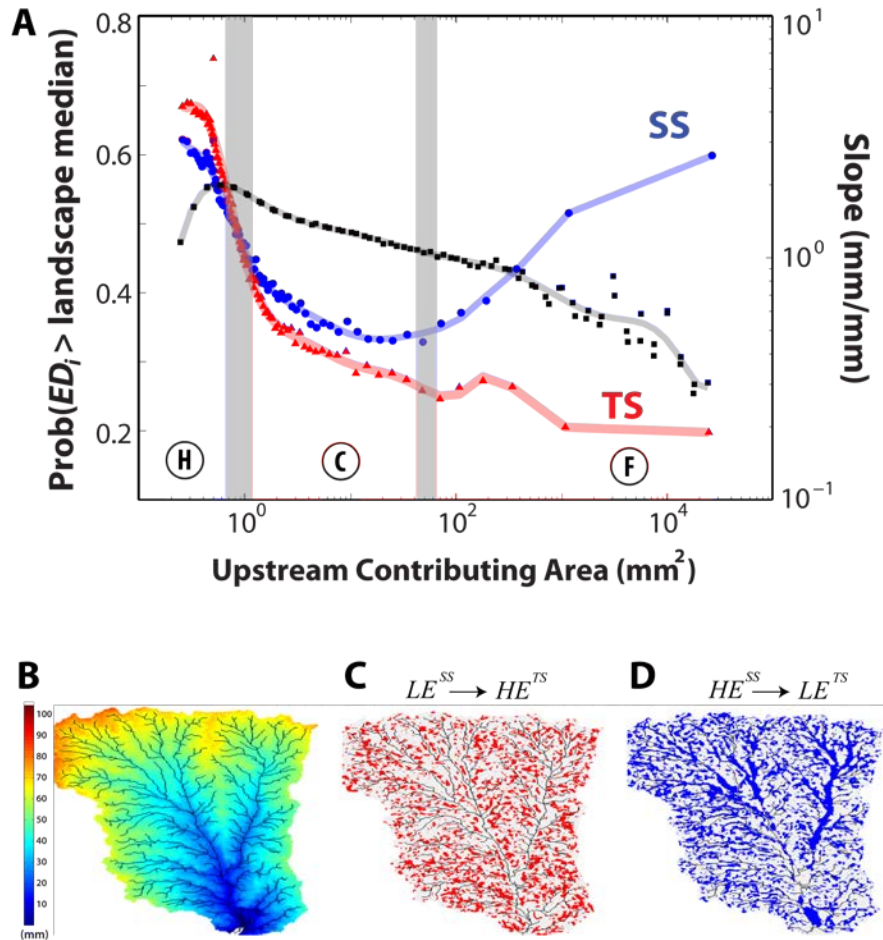
489 **Fig. 4. Spatial patterns of erosion in steady state (SS) and transient state (TS) landscapes.** Locations
 490 (black) of the highly eroding pixels (with local erosion depth above the landscape median) superimposed
 491 on the DEMs for (A) SS and (B) TS. The distinct patterns of erosion corresponding to SS and TS are
 492 apparent by visual inspection. Notice for example the lack of highly eroding pixels within the channel
 493 network at TS in comparison to SS.

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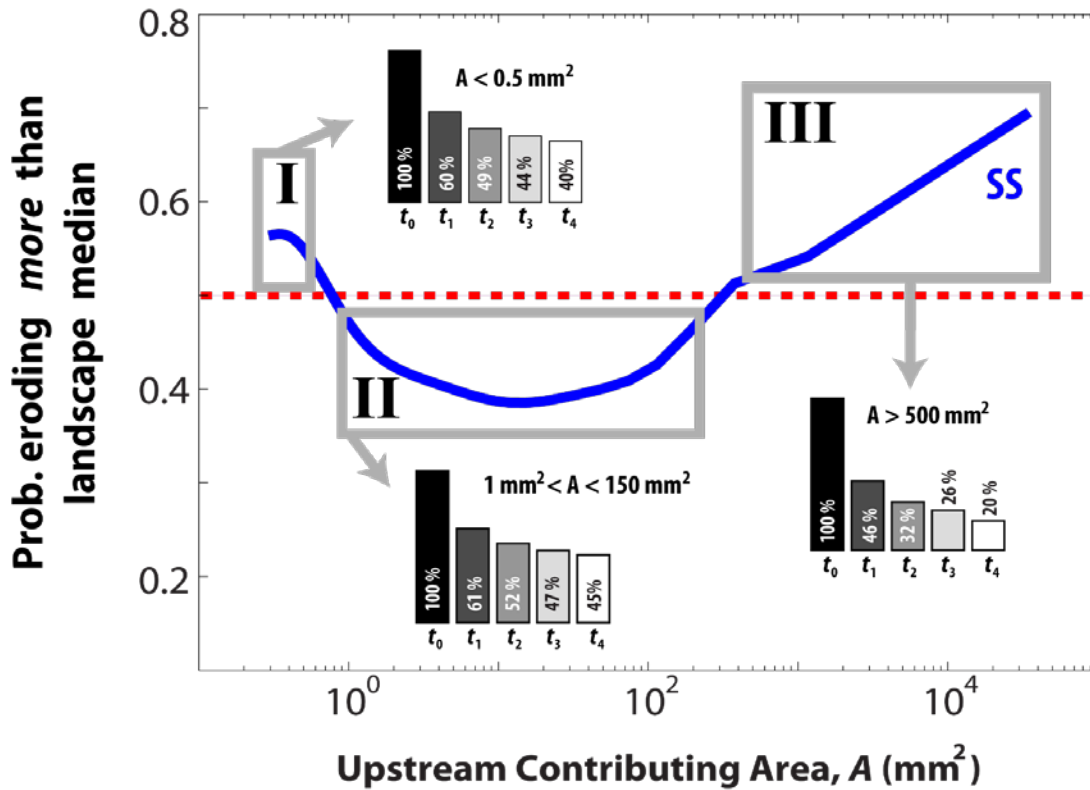
499 **Fig. 5. Scale-dependent reorganization of the landscape.** (A) E50-area curves for both SS (blue) and
 500 TS (red). The slope-area curve for SS (black) is also shown and the three geomorphic regimes of
 501 hillslopes (H), colluvial (C), and fluvial (F) are noted. After the onset of TS conditions, we observe
 502 increased erosion in response to increased precipitation, with this trend inverted within the colluvial
 503 regime where erosion systematically decelerates downstream. In the channels, a sediment-flux dependent
 504 incision behavior is observed, as depicted by the divergence of the E50-area curves in the fluvial part of
 505 the landscape. The vertical grey bars depict the transitions in the behavior of E50-area curves when SS
 506 and TS are compared. (B) DEM of a drainage basin from the experimental landscape with the river
 507 network superimposed as a reference. (C) Locations in the basin (red pixels) where the erosion depth has
 508 shifted from a value below the landscape median at SS (LE^{SS}) to above the landscape median at TS
 509 (HE^{TS}), showing that increased erosion occurs predominantly on hillslopes. (D) Locations in the basin
 510 (blue pixels) where the erosion depth has shifted from a value above the landscape median at SS (HE^{SS}) to
 511 below the landscape median at TS (LE^{TS}), showing that decreased erosion occurs predominantly within
 512 the fluvial regime.

513 **Supplementary Material**

514 **Scale-dependent erosional patterns in steady and transient state landscapes**

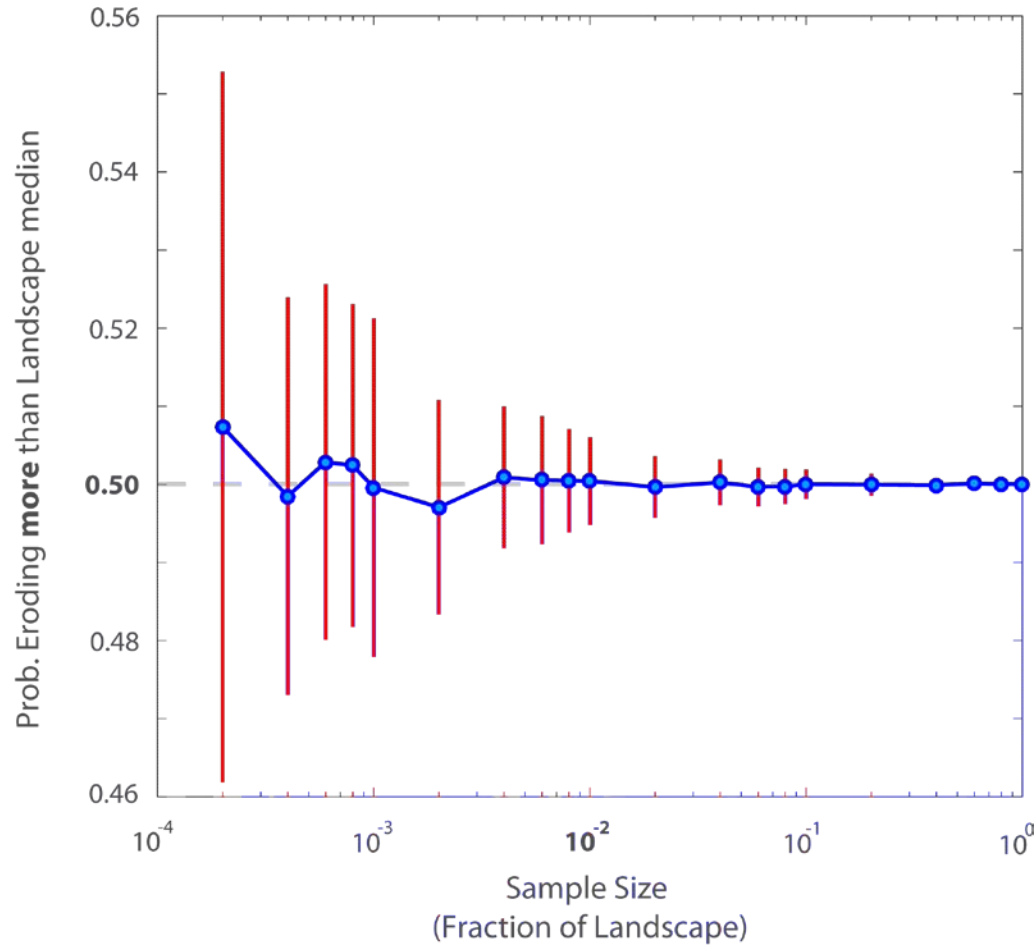
515 Alejandro Tejedor, Arvind Singh, Ilya Zaliapin, Alexander L. Densmore, Efi Foufoula-Georgiou

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518 **Fig. S1. Dynamic Landforms at Steady State.** The shape of the E50-area curve reveals that the
 519 likelihood of eroding more (or less) than the median of the landscape is nonlinearly related to the
 520 upstream contributing area, A . We examine the dynamic nature of steady-state landscapes within three
 521 ranges of upstream contributing areas: (I) $A < 0.5 \text{ mm}^2$, with a higher likelihood of eroding more than the
 522 median of the landscape; (II) $1 \text{ mm}^2 < A < 150 \text{ mm}^2$, with a lower likelihood of eroding more than the
 523 landscape median; (III) $A > 500 \text{ mm}^2$, with a higher likelihood of eroding more than the landscape median.
 524 We identify at a given time (t_0) the location of all the pixels on the landscape within each of the three
 525 ranges defined above (100%). For each subsequent topography (measured 5 min apart), we compute the
 526 percentage of pixels on those locations, which are still characterized by A in the same interval as initially
 527 defined. The inset plots show that, in each area range, a significant percentage of pixels change their
 528 upstream contributing areas over time, illustrating the dynamic nature of steady-state landscapes.



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530 **Fig. S2. Estimation of the probability of erosion larger than the landscape median at SS for**
 531 **different sample sizes.** Blue circles correspond to the estimated probability of eroding more than the
 532 median of the landscape (Y axis) by using 100 randomly selected samples of a given size (X axis). The
 533 red lines correspond to standard deviations estimated from the 100 samples. Note that to construct the
 534 E50-area curve we used 100 bins, which have a constant sample size equal to 0.01 fraction of the
 535 landscape. From the results corresponding to sample size equal to 10^{-2} shown in this figure, we can
 536 conclude that the patterns depicted by the E50-area curves (see Fig. 3 and 4 in the main text) are
 537 statistically significant.

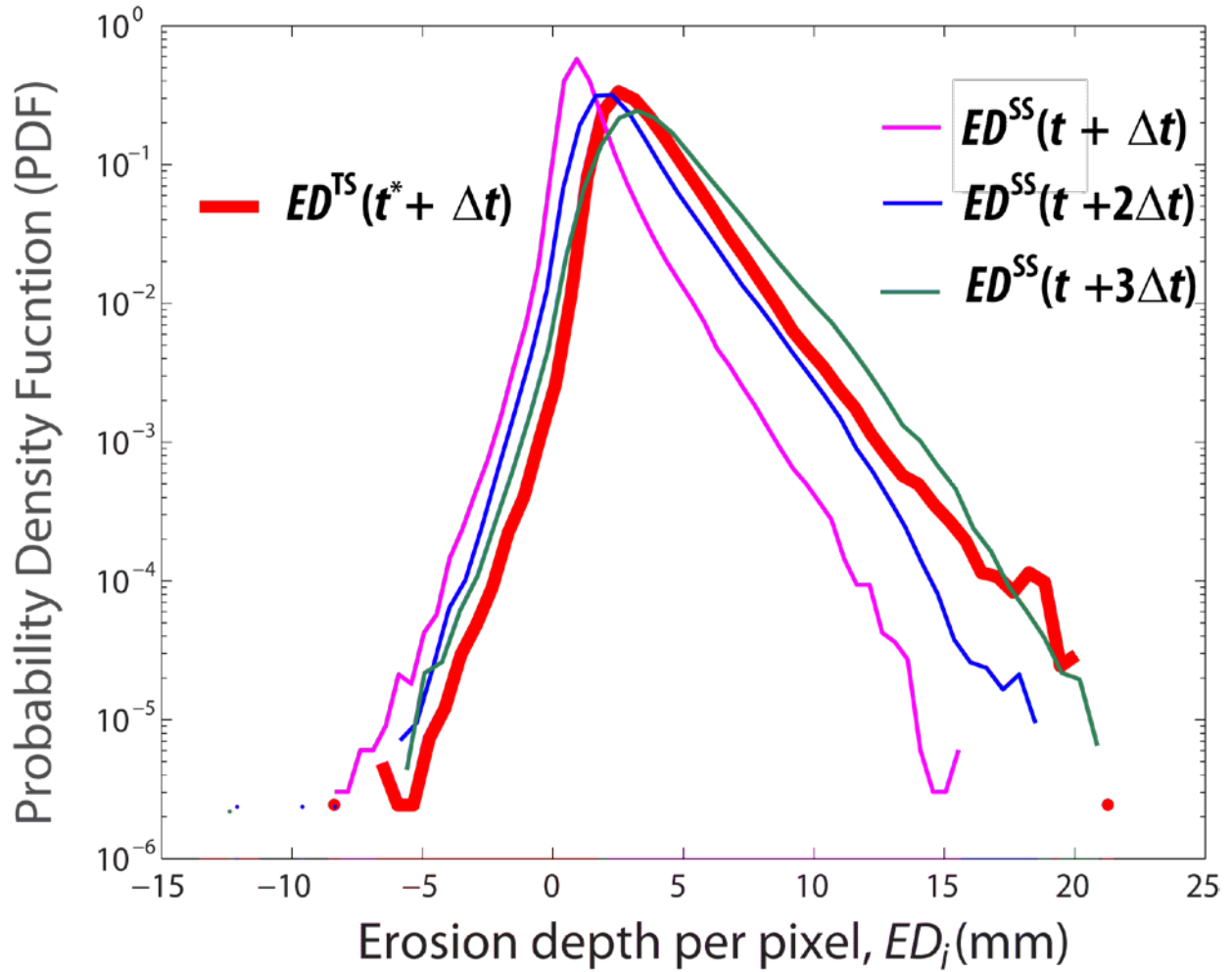
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544 **Fig. S3. Comparison of the steady-state (SS) and transient-state (TS) landscapes in terms of the**
 545 **aggregate statistics of erosion depth.** Probability density functions (PDFs) of erosion depth per pixel,
 546 ED_i , in the TS landscape, subject to a five-fold increase in precipitation intensity during 5 minutes (Δt)
 547 starting at time t^* (red curve), and the SS landscape during 5 (magenta), 10 (blue), and 15 (green)
 548 minutes.

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