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1 Scaling laws for rivers and runoff

1.1 Weathering and runoff

Over the long term (10^5 – 10^9 yr), the slow processes of the *rock cycle* dominate the carbon cycle.

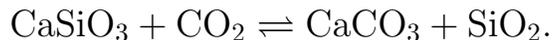
We have already discussed volcanism as the long-term *source* of CO_2 , and burial as the long-term *sink*.

Prior to burial, rocks are chemically weathered (e.g., leached). Dissolved carbon then becomes part of groundwater and river flows, the oceans, and—ultimately—sedimentary rocks.

Thus weathering may be thought of as the initiation of the burial sink.

With respect to the carbon cycle, the most important of the chemical weath-

ering reactions reads schematically as follows [1–3]:



A similar reaction may be written by substituting Mg for Ca.

Left-to-right, such reactions represent the uptake of CO_2 from the atmosphere, its transformation to HCO_3^- during weathering of silicate minerals, and its eventual precipitation and burial in the oceans as carbonate minerals.

Right-to-left, the reaction represents metamorphism and magmatism and the subsequent transfer of CO_2 back to the atmosphere and oceans by volcanism and related processes.

In this lecture we consider aspects of transport implied in the forward reaction.

From the viewpoint of the carbon cycle, transport is especially important if the reaction is *transport-limited*, i.e., if the rate of the forward reaction is determined more by transit times than by the time it takes for dissolution.

In this idealization, we imagine that a raindrop immediately dissolves minerals, and we seek to understand the geometry of the path taken by the raindrop were it to continue to the ocean.

We could proceed to associate time scales with travel paths, but we shall limit ourselves to purely geometric considerations.

1.2 Drainage basins and river networks

Our idealized raindrop falls in a *drainage basin*, and eventually flows through a river network.

River networks are among the most beautiful of Nature's large-scale *scale-invariant* phenomena.



Image courtesy of NASA.

To see what we mean by scale-invariant, we briefly return to random walks.

1.3 Scale invariance of random walks

Define the rms excursion $r = \langle x^2(t) \rangle^{1/2}$. We have previously shown that

$$r \propto t^{1/2}.$$

Now rescale time $t \rightarrow bt$ and note that

$$r(t) = b^{-1/2}r(bt).$$

This simple manipulation yields a remarkable observation: the statistics of the random walk are unchanged by the simultaneous rescaling

$$x \rightarrow b^{1/2}x, \quad t \rightarrow bt.$$

This means that the random walk is statistically equivalent at all scales, e.g.

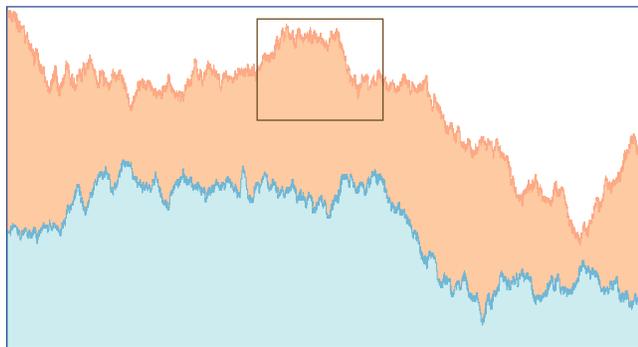


Image by MIT OpenCourseWare.

Here $b = 1/5$ and the inset is “blown up” by stretching the horizontal axis by a factor of 5 and the vertical axis by $\sqrt{5}$.

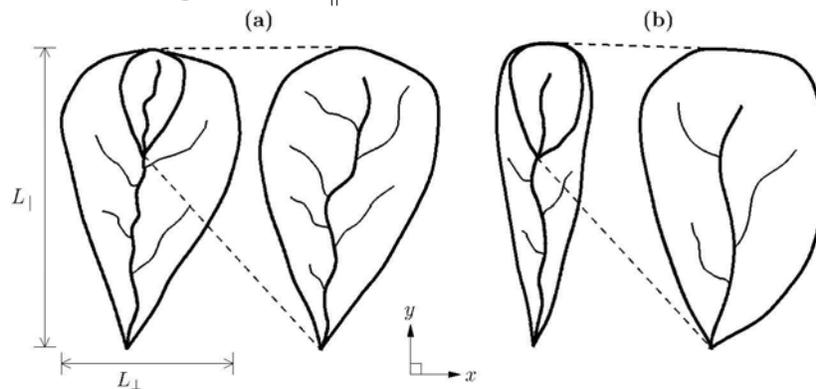
[Another example: go to any financial website that provides graphs of market fluctuations at a time scale of your choosing (days, weeks, months, years). Note that aside from long-term trends, all graphs look alike!]

Although we present the random walk as an example of scale-invariance, note that space and time do not scale in the same way.

1.4 Allometric scaling

River basins exhibit a similar phenomenon: they too have statistically similar shapes at all scales, but their dimensions scale differently.

We refer to the two lengths as L_{\parallel} and L_{\perp} :



The area a is

$$a \propto L_{\parallel} L_{\perp}.$$

Measurements made from maps typically show

$$L_{\perp} \propto L_{\parallel}^H, \quad 1/2 \lesssim H \lesssim 1$$

and therefore

$$a \propto L_{\parallel}^{1+H}$$

The case $H = 1$ in (a) yields geometric similarity or self-similarity: no matter what the size of a , all basins “look alike.”

The case $H \neq 1$ in (b) is called *allometric scaling* (as opposed to “isometric”): dimensions grow at different rates.

Specifically,

$$\frac{L_{\perp}}{L_{\parallel}} \propto L_{\parallel}^{H-1} \propto \left(a^{\frac{1}{1+H}}\right)^{H-1} = a^{-\frac{1-H}{1+H}}.$$

Since observed values of H fall within $0 < H < 1$,

$$\frac{1-H}{1+H} > 0.$$

Therefore

- large river basins tend to be long and thin; and
- small river basins tend to be short and fat.

Upon appropriate rescaling, however, they all look the same.

1.5 Size distribution of river basins

Suppose we stand at a point x_0 chosen at random on a landscape. What is the size of the area a that drains into it?

We could estimate a by walking uphill from x_0 , always following the steepest path. That brings us to a drainage divide, providing an estimate of L_{\parallel} .

Obtaining the full area a , however, requires more work. A particularly labor intensive method would be to create a grid of, say, 1 m, and to place a person at each grid site above x_0 . We then ask each person to follow his/her path of steepest *descent* from one grid site to the next. Then if N people eventually arrive at x_0 , the drainage basin has size N m².

More generally, what is the probability distribution $P_a(a)$ of drainage areas?

To answer this question we create a model of a landscape made of random bumps. The bumps are smooth on a small scale but otherwise independently chosen from some well-behaved distribution like a Gaussian.

We then *tilt* the landscape so that all paths of steepest descent are always *directed* in the direction of the tilt.

We then populate the landscape as before, and follow each path of steepest descent. Supposing that the square grid is oriented 45° to the tilt direction, each step down will also be a step to the left or right, and the coalescence of the various paths will look like this:

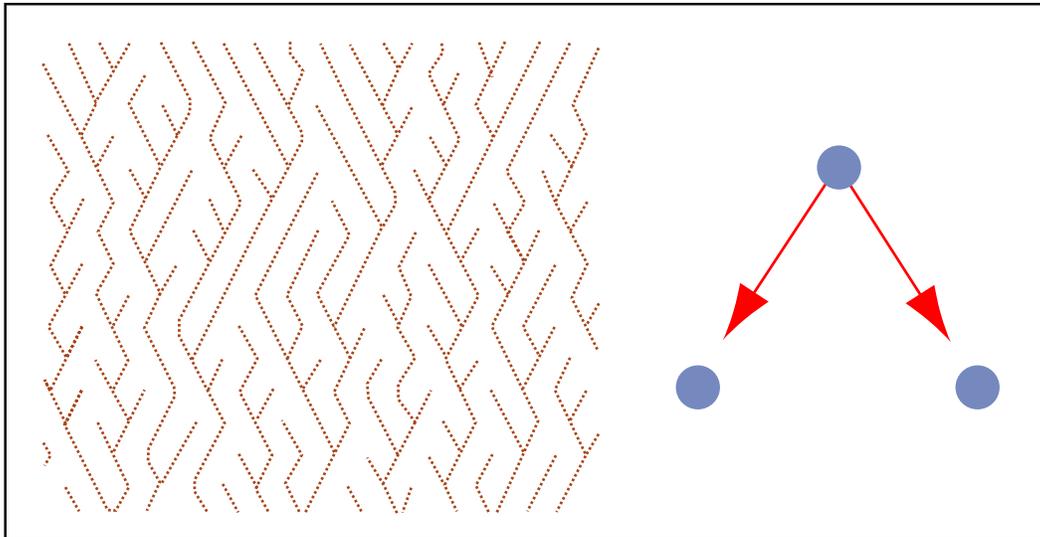


Image by MIT OpenCourseWare.

If we then trace out any basin, we find that its left and right boundaries are particular realizations of a *random walk*.

This is Scheidegger's 1967 model of river networks [4].

Since for a random walk we have $\langle x^2 \rangle^{1/2} \propto t^{1/2}$, we substitute

$$t \rightarrow L_{\parallel}, \quad x \rightarrow L_{\perp}$$

and conclude

$$L_{\perp} \propto L_{\parallel}^{1/2} \quad \Rightarrow \quad a \propto L_{\parallel}^{3/2}.$$

Since our random walks are always *directed* toward the bottom boundary, the length l of the longest stream in each basin scales like

$$l \propto L_{\parallel}$$

and therefore

$$l \propto a^{2/3}.$$

Real rivers exhibit a similar scaling law, called *Hack's Law* [5]:

$$l \propto a^h, \quad 0.57 \lesssim h \lesssim 0.60.$$

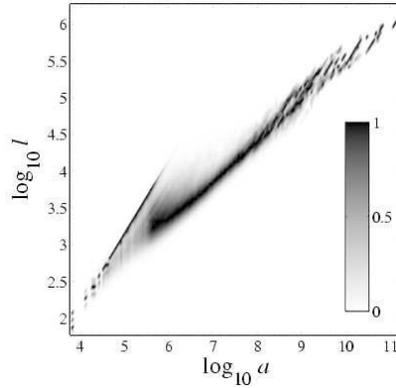


Image courtesy of USGS.

The correspondence between the two suggests that our model is reasonable.

To find $P_a(a)$, we write

$$\begin{aligned}\phi_l(y) &= \text{left basin boundary} \\ \phi_r(y) &= \text{right basin boundary}\end{aligned}$$

and assume that they both start at $y = 0$. Note that the difference

$$\phi(y) = \phi_l(y) - \phi_r(y)$$

is itself a random walk that not only begins at $y = 0$ but also ends at $y = 0$.

We ask a precise question: *What is the probability that $\phi(y)$ returns to its initial position for the first time after n steps?*

This is the classic *first-return* or *first-passage time* of a random walk. The answer, for large n , is [6, 7]

$$P(n) = \frac{1}{2\sqrt{\pi}}n^{-3/2}.$$

Since our random walks are directed, the main steam length $l \propto n$. Therefore

$$P_l(l) \propto l^{-3/2}.$$

Recall that we seek the area distribution $P_a(a)$. We assume a continuous distribution of areas and seek

$$P_a(a)da = \text{Prob}(a \text{ is between } a \text{ and } a + da).$$

We assume that $P_l(l)$ is also defined continuously. Then, since $l = l(a)$, the probabilities $P_a(a)$ and $P_l(l)$ are related by

$$P_a(a)da = P_l(l)dl.$$

Recalling that $l \propto a^{2/3}$, we have

$$\begin{aligned} P_a(a) &= P_l(l(a)) \frac{dl}{da} \\ &\propto (a^{2/3})^{-3/2} a^{-1/3} \\ &= a^{-4/3}. \end{aligned}$$

Real rivers exhibit

$$P_a(a) \propto a^{-\tau}, \quad \tau = 1.43 \pm 0.02,$$

suggesting once again that our model is reasonable.

1.6 Scaling relation

Gathering our results, we have

$$\begin{aligned} l &\propto a^h \\ P_a(a) &\propto a^{-\tau} \\ P_l(l) &\propto l^{-\gamma} \end{aligned}$$

where, comparing Scheidegger's random-walk model to real observations, we have

| Exponent | Scheidegger | Real world |
|----------|-------------|-----------------|
| h | $2/3$ | 0.58 ± 0.02 |
| τ | $4/3$ | 1.43 ± 0.02 |
| γ | $3/2$ | 1.8 ± 0.1 |

Since we are looking at areas and lengths, we expect that, whatever their real values, the exponents h , τ , and γ should be related to each other. We find this relation by writing

$$\begin{aligned} P_a(a) &= P_l(l(a)) \frac{dl}{da} \\ &\propto (a^h)^{-\gamma} a^{h-1} \\ &= a^{-[1-h(1-\gamma)]}, \end{aligned}$$

which yields

$$\tau = 1 - h(1 - \gamma).$$

This is an example of a *scaling relation*: an algebraic relationship that gives the explicit dependence between exponents. In this case, it says that we need only know two exponents to obtain the third. (Further work [8,9] shows that there is only one independent exponent.)

Our scaling relation is readily verified by substituting the value for Scheidegger’s model:

$$\frac{4}{3} = 1 - \frac{2}{3} \left(1 - \frac{3}{2} \right)$$

As for the real world, we have

$$1.43 \simeq 1 - 0.58(1 - 1.8) = 1.46.$$

Overall we see that the statistical geometry of river networks—the power-law scaling, and the relations between the exponents—is well described by Scheidegger’s random walks.

Note that we have said nothing about how real rivers form.

Instead we note that their tendency to aggregate (i.e., connect) as they flow downhill is the main ingredient necessary to account for their principal geometric features *after* they form.

We suspect that this reflects the universal properties of random walks: i.e., that the mean square fluctuation in one dimension scales roughly like the mean fluctuation in the other.

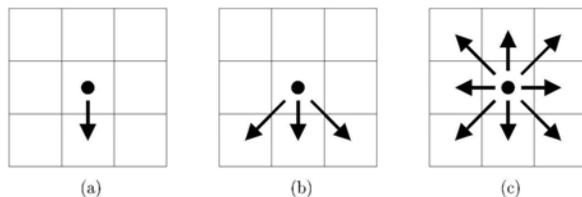
If this is true, it means that natural landscapes contain no particularly special features that suggest that the typical paths of steepest descent are *unlike* random walks.

That the Scheidegger model does not capture the correct values of the exponents τ , h , and γ suggests nevertheless that something important is missing.

We proceed to consider what that might be.

1.7 Universality classes

Let us consider our random-walk model as a member of a wider class of models based on the kind of path taken by flowing water:



- (a) Non-convergent.
- (b) Directed random walks (Scheidegger).
- (c) Undirected random walks.

Now consider Hack's law $l \propto a^h$.

The trivial non-convergent case (a) yields $h = 1$.

Directed random walks (b) yield $h = 2/3$.

Undirected random walks (c) yield $h = 5/8$ [10].

Remaining exponents are obtained from our previous scaling relation, augmented by the additional relation $\tau = 2 - h$ [8, 9].

Each of these cases may be considered *universality classes*. These classes are delineated by qualitative conditions: here, the way in which flowing water can aggregate. These qualitative conditions then lead to specific quantitative predictions of exponents.

Which universality class is “correct”? One could argue that undirected random walks are the most realistic class, and that it is no surprise that their Hack exponent, $h = 5/8$, is the closest to the observed $h \simeq 0.58$.

Although such reasoning may possibly be valid, it misses the main lesson: *Aggregating random walks capture the main features of river network geome-*

try.

1.8 Null models

Our model of aggregating random walk models may be thought of as a *null model*.

A null model is a model which ignores nearly all details of a real process but reproduces some essential characteristics of that process.

Here we have found that the scaling laws for river networks are essentially consistent with our null model.

In doing so, we could conclude that the details do not matter.

We might however suggest that the model requires more ingredients to get the exponents “right.”

In that way we would claim that a mismatch of exponents suggests that the null model is an insufficient representation of reality and that, e.g., a key physical process is missing from the model.

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