# Dynamic Functional Connectivity Resolves Brain Integration-Segregation Trade-off Under Costly Links


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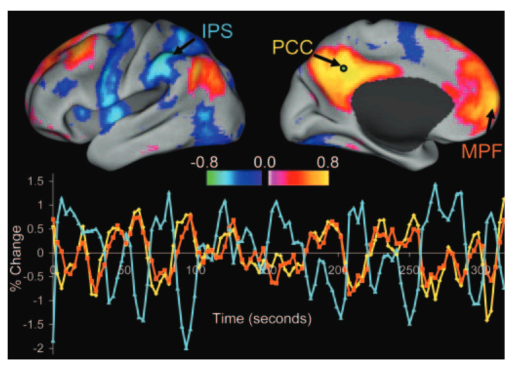
## Introduction

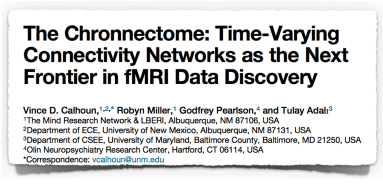
- **Functional connectivity** of the resting state describes patterns of correlation between distant regions working together

- Usually described as static, time-averaged network but it changes relentlessy through time as described by **dynamic Functional Connectivity (dFC)** analyses

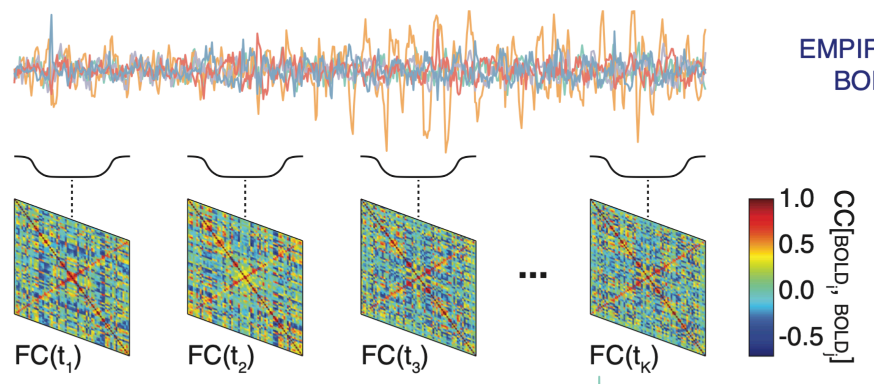
- dFC fluidity is not only ubiquitous, it serves as **biomarker** of efficient cognitive performance and tracks different conditions (aging, pathology...)

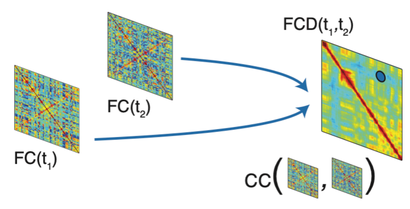



*Fox et al. (2005)*

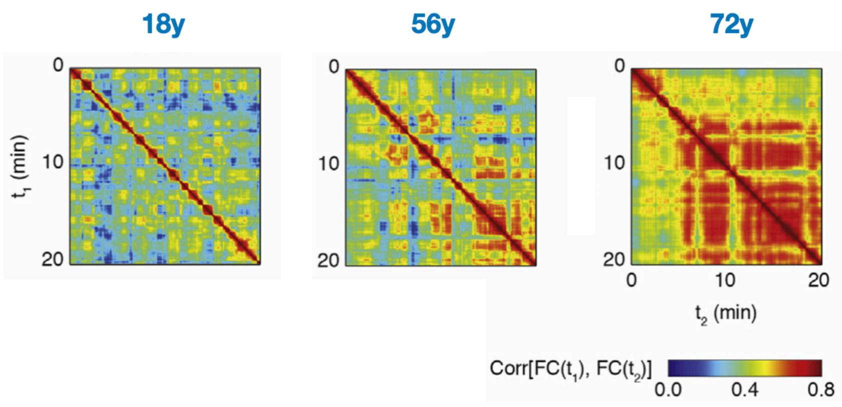

The Chronnectome: Time-Varying Connectivity Networks as the Next Frontier in fMRI Data Discovery

*Calhoun et al. (2015)*




*Recurrence analyses to detect structure in temporal variability*




*Example: dFC slows down with aging or sleep deprivation, correlating with degraded cognitive assessments*

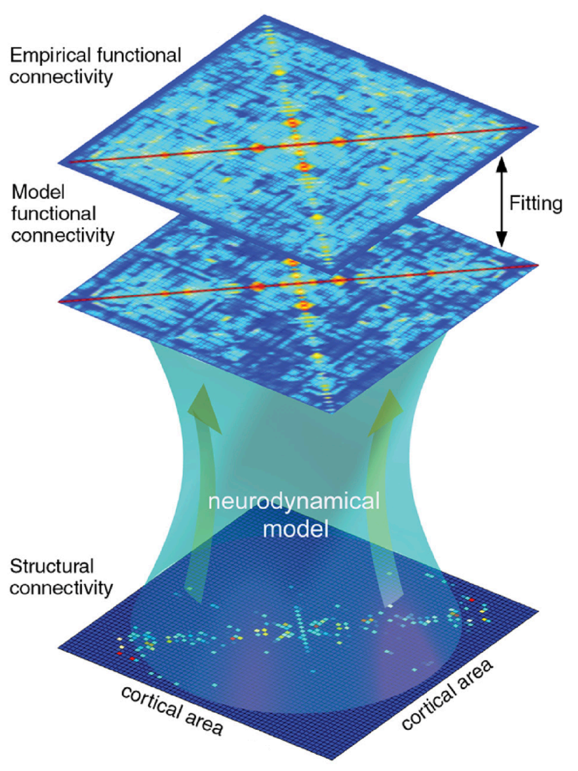
*Battaglia et al. NeuroImage (2020)*

*Lombardo et al. NeuroImage (2020)*

Functional connectivity supposedly reflects **inter-regional interaction and exchange of information**. If the aim of establishing FC is to enable communication why not generating a stable functional network infrastructure, optimized for information exchange efficiency?

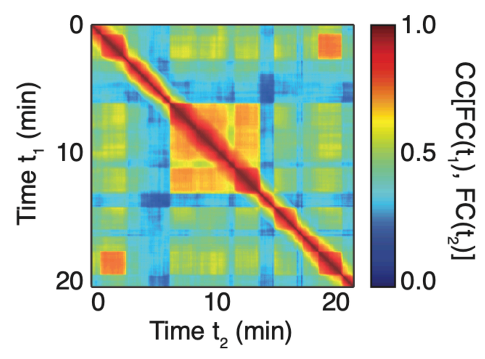
**In other words, why dFC should be "d" ?**

## "Why" as "how to": dFC is naturally occurring




*dFC recurrence matrix from simulated rs*

*Hansen et al. NeuroImage (2015); Pathak et al., PLoS Biology (2026)*




- **Mean-field models** of whole brain dynamics can be used to emulate resting state dynamics. Simulations spontaneously give rise to a rich dFC because of the **sampling of an internal repertoire of dynamical states** a

- Best fit to empirical dFC found through a dynamic working point roaming between critical lines as an effect of fluctuating arousal

- Thus dFC is "d" "why"... **it would be unlikely to be otherwise**

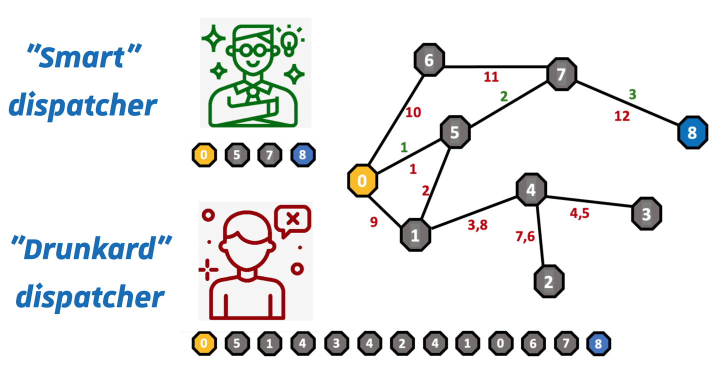
## "Why" as "what for": dFC as an asset for info flow?

- Consider **FC networks as a communication infrastructure system** on which some unspecified **"information" can flow** moved by some unspecified dispatcher process. Information can move over a **static graph of FC** but also over a **temporal graph of dFC**

- Suppose that "keeping on" a **FC link at a certain time has some cost**, e.g. metabolic cost of high synchrony. We use **binary undirected networks** for simplicity (one link "on" at time *t* = cost 1; Tot cost = tot number of links over space *and* time)

If the system disposes of a **finite amount of resources**, how should it better spend them to dispatch info efficiently? By creating **fewer but long-lasting optimized links?** or, **at equal cost and duration**, **more transient links?** Is there an **optimum tradeoff** ?

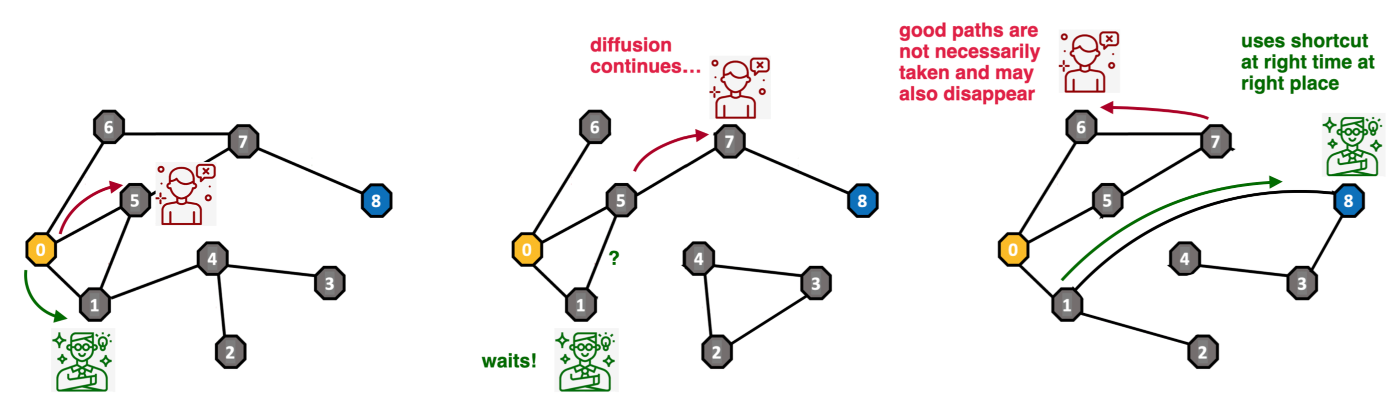
- We study **two strategies for info dispatch** on static and temporal graphs: the **"smart" scenario** corresponds to an *upper bound*, the **"drunkard" scenario** to a *chance expectation*



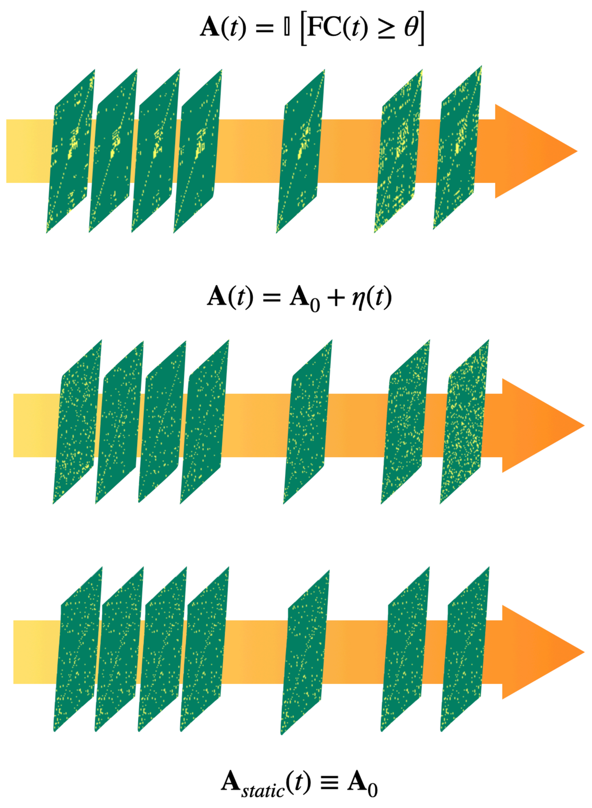

A smart dispatcher always chooses the **shortest path** to move info from a node to another (here "0" to "8")

A drunkard dispatcher performs a **random walk** on the graph until the target is found

Even more complicated on a temporal net: **Time-respecting paths !**




## How far and how fast can dFC diffuse information?



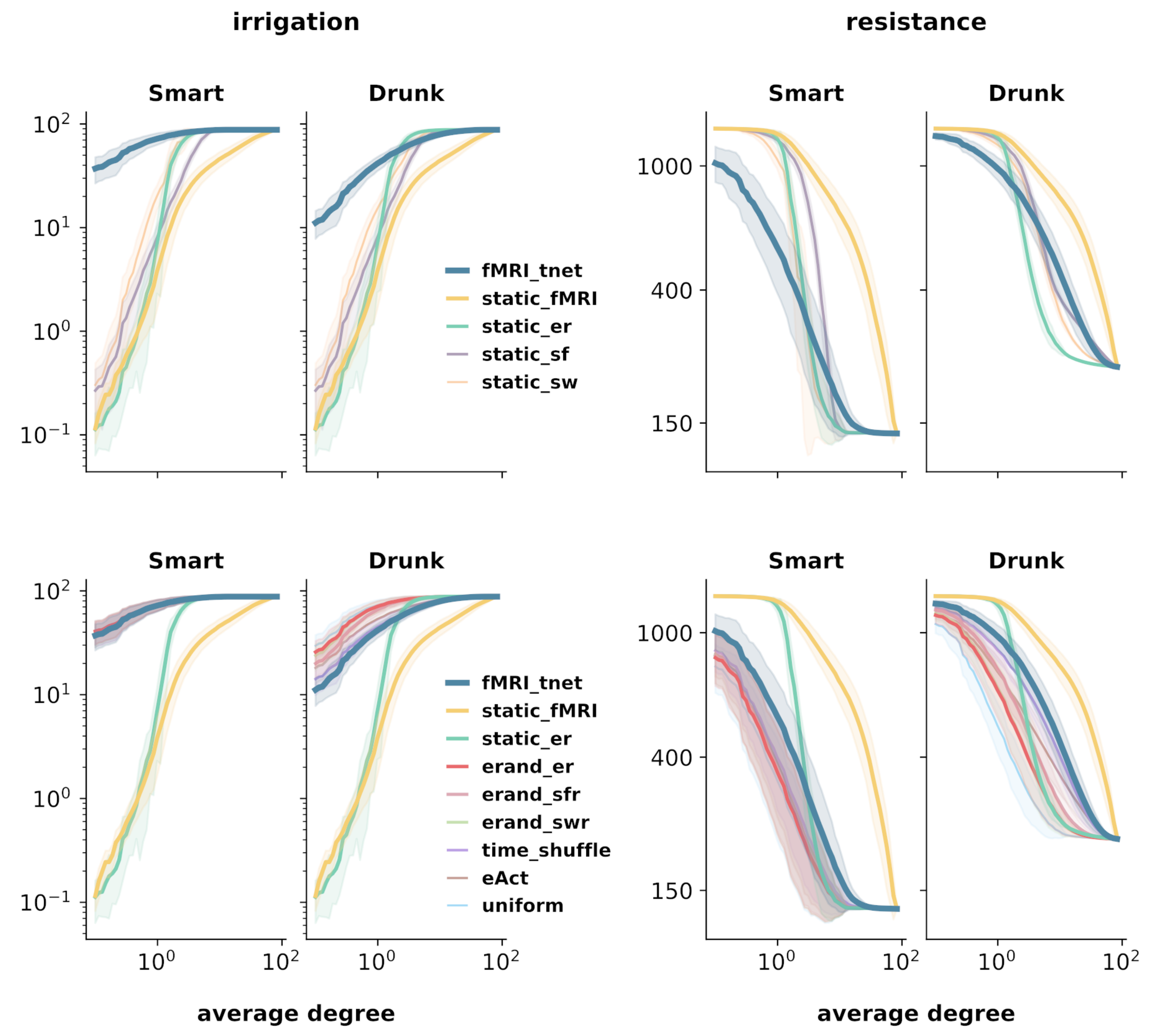

A binary temporal network ***A(t)*** is constructed from an **empirically measured dFC stream** from 20 min of human BOLD rs fMRI (*time window 20 s, data from Human Connectome Project, 99 subjects*) Application of a **sharp threshold** ***θ*** to control the obtained average degree. ***$A_{static}$(t)*** is constructed from an **average temporal network frame**, rebinarized to obtain a temporal network with the **same cost**

We compare empirical **fMRI_tnet** dFC streams with an equal cost **static_fMRI** version. In addition we have a variety of <u>null models</u>, both static (e.g. same density stantc Erdös-Rényi, scale-free or small-world) and dynamic. In **edge-randomized (erand)** link density is maintained frame-by-frame but links are randomly rewired, while in **uniform** every frame is regenerated from scratch with a homogeneous static-like link density in every frame. In **time shuffle**, frames are kept identical but time-shuffled. Finally in **edge-activation (eAct)**, every link is randomly generated with a link-specific activation probability matched to empirical.

### Integrative diffusion metrics

**Irrigation,** i.e. the **amount of nodes reachable by info** initially at a source node over a given horizon of time (*T* = ~10³ frames, equivalent to empirical rs sessions below)

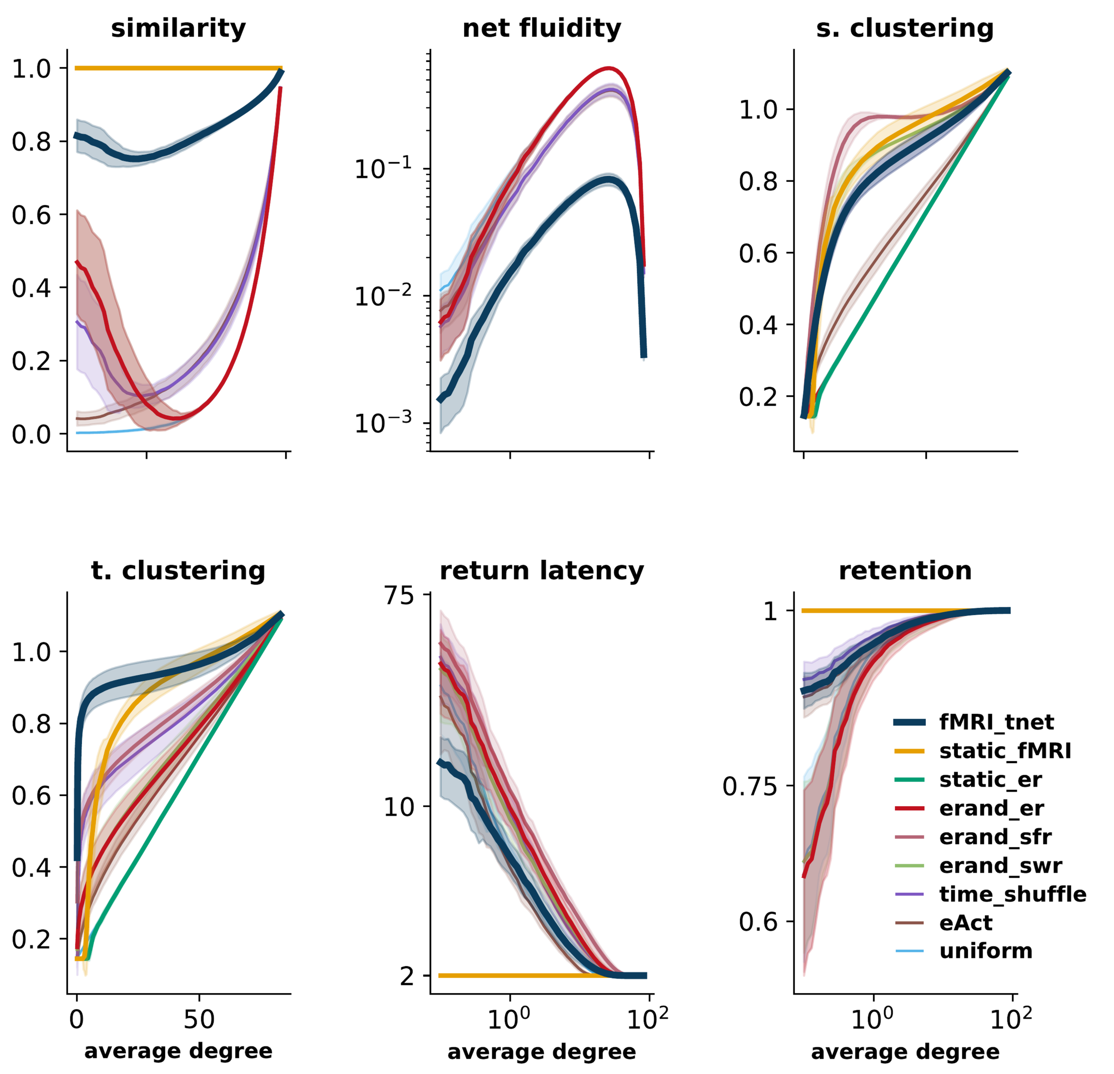
**Resistance to information diffusion** measured as the **time needed for info to reach a target node**, averaged over all possible targets (targets that are not reached over the observation time *T* contribute a **penalty** of *T*+1)




- **Static dFC** (empirical and nulls) has **lower Irrigation** and **higher resistance** than empirical dFC, **when the budget for tnet construction is restrained**

- More **random dynamic models** however achieve **even better irrigation and resistance** than empirically observed dFC!

## An optimal tradeoff between integration and segregation?

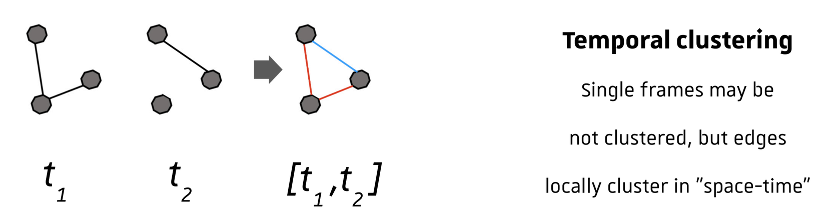



- Information processing requires as well the capability to **segregate information** for processing by localized sub-networks, information must thus be retained for a sufficient time before completely leaking away.

### Segregative diffusion metrics

**Similarity**, or how similar is a network frame to the next
**Net fluidity,** fraction of links changing from frame to frame

**Spatial clustering**, the conventional clustering coefficient
**Temporal clustering**, the clustering coefficient of an aggregate of Δ consecuitve time frames




**Return latency**, the fastest time needed for information to come back to a source node, after having left it
**Retention**, the fraction of currently neighboring nodes that are still neighbors at the next frame.

- **Static dFC** has **100% similarity and retention** and **minimum return latency** by construction. Temporal clustering matches spatial clustering.

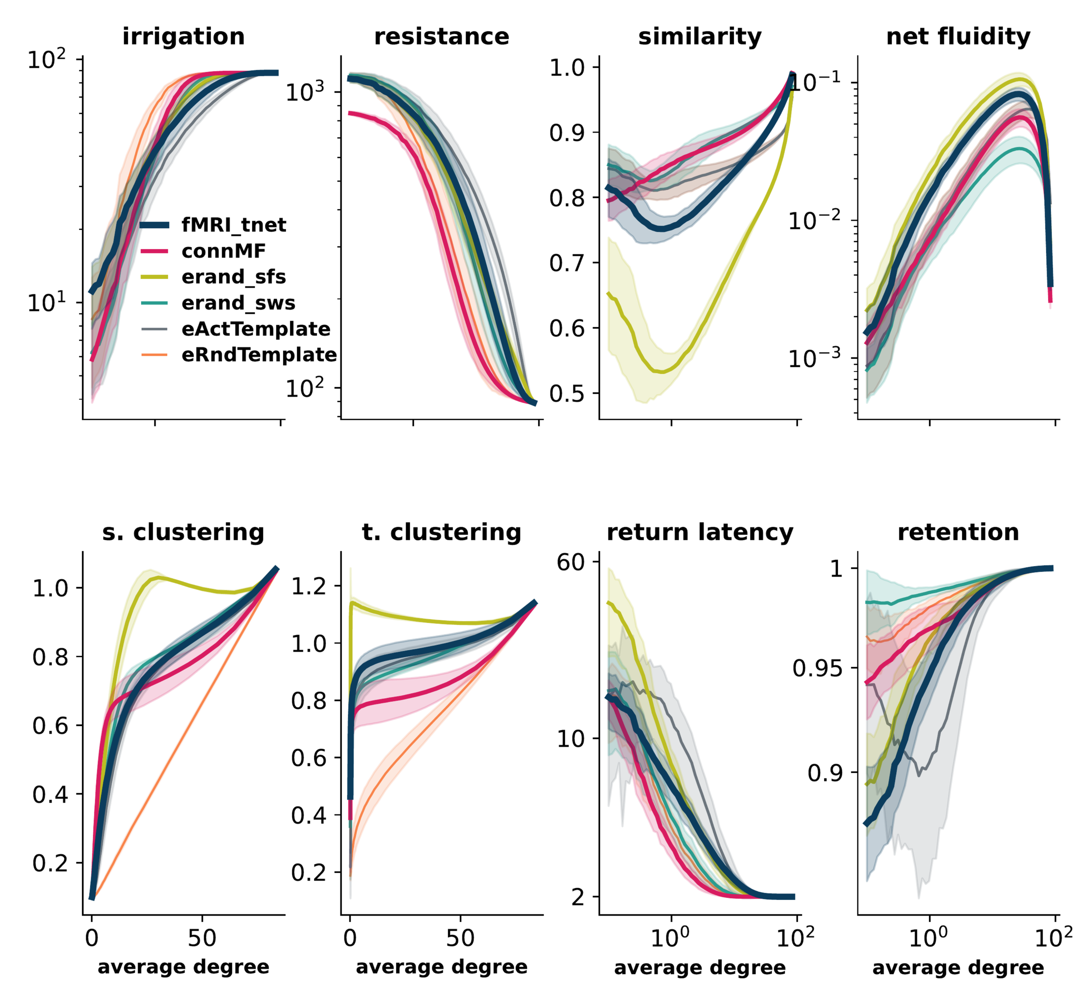
- **Empirical dFC** has **near-static similarity and retention** and **very low return latency**, better then more random null models. **Spatial clustering is lower** than static, but **temporal clustering is larger.**

## Where this tradeoff comes from?

- **Staticized nulls** add persistent templates and **recover part of empirical quasi-staticity**, but miss the full integration-segregation profile.

- ConnMF, a c**onnectome-based mean-field model** with fluctuating working point / critical roaming, gives the **best qualitative trade-off**: high spatial and temporal clustering with strong integration and segregation.

- Remaining mismatch: **simulated dynamics remain too persistent** / offset from empirical dFC, suggesting an additional decorrelating or renewal mechanism?




### Some open questions

- What is the **nature of "link cost"**, metabolic, linked to synchronization?
- Are null models capturing the **auto- and cross-correlation properties of BOLD** signal outperforming graph-based staticized nulls?
- Are fluctuations in network density of empirical dFC interpretable as an **avalanching phenomenon**? Power-laws? Link to **percolation**?
- Are our info flow features useful as **biomarkers of cognitive (dys)function**?