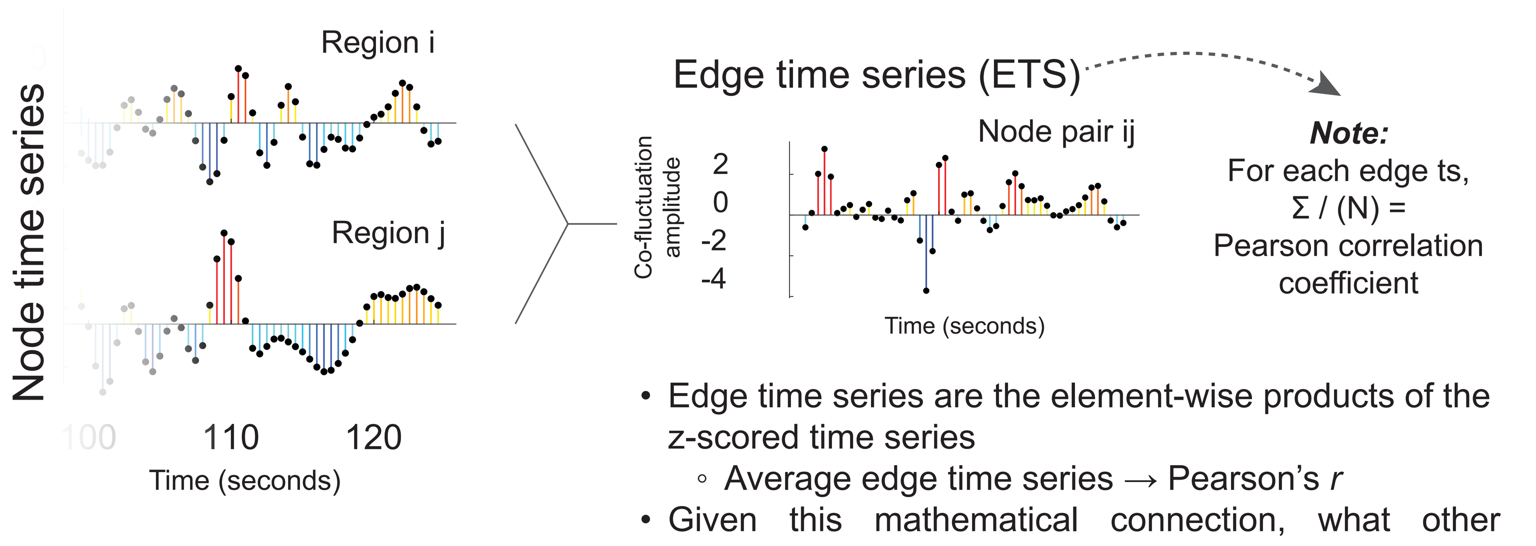
On the static and dynamic features of edge time series

Joshua Faskowitz[1], Tyler Morgan[1], Daniel A. Handwerker[1], Javier Gonzalez-Castillo[1], Peter A. Bandettini[1,2]

[1] Section on Functional Imaging Methods,
[2] Functional Magnetic Resonance Imaging Core Facility,
National Institute of Mental Health, Bethesda, USA

Introduction

- Functional magnetic resonance imaging (fMRI) has repeatedly shown that BOLD signals will fluctuate across the cortex during task-free conditions
  - Fluctuating regions are often compared using **Pearson correlation**
  - Taking correlation between all region pairs forms a correlation, i.e., *functional connectivity*, matrix.
- Measuring the **dynamic nature of correlations** is increasingly popular; can reveal connectivity states[5] and transients[11]
- **Edge time series**[3,16] render connectivity dynamics at the temporal resolution of the input time series
  - Recently, it has been shown that features of edge time series can be partially explained with features of static correlation[9,12,13].
- Here we further explore the relationship between static versus dynamic edge time series features.



- Edge time series are the element-wise products of the z-scored time series
  - Average edge time series → Pearson's r
- Given this mathematical connection, what other relationships exist between time-average correlation and what we read out from edge time series?

Methods

- **Simulated data**
  - Time series generated with a 2-state Markov chain, convolved with a canonical HRF for five-second stimulus and bandpass filtered (0.008-0.08 Hz)
  - Target covariance patterns were enforced on randomly generated and uncorrelated channels by projecting the data onto the axes of the eigen-decomposed covariance[10]
    - Using this method, we can control coupling (i.e., correlation) between two channels
  - Randomly generated target covariance using the stochastic block model[1] — a generative network model that allows for planted community structure with parameterized weight and edge existence
- **Real data**
  - Human Connectome Project resting-state data (0.72 TR, 1200 TRs, ~15 mins)
  - Minimally pre-processed[4]: motion, distortion, bandpass, first/last 50 TRs discarded
  - Nuisance regressed using aCompCor[2] components (5 WM, 5 CSF) and 24 motion parameters. Time series constructed by averaging vertex data within 200 node of Schaefer parcellation[15], at each time point, using Connectome Workbench
- **Edge time series**
  - Computed via the element-wise product of two z-scored time series; sum of which is correlation
  - RSS: root of the sum of squares of all edge time series magnitudes, taken at each time point

Results

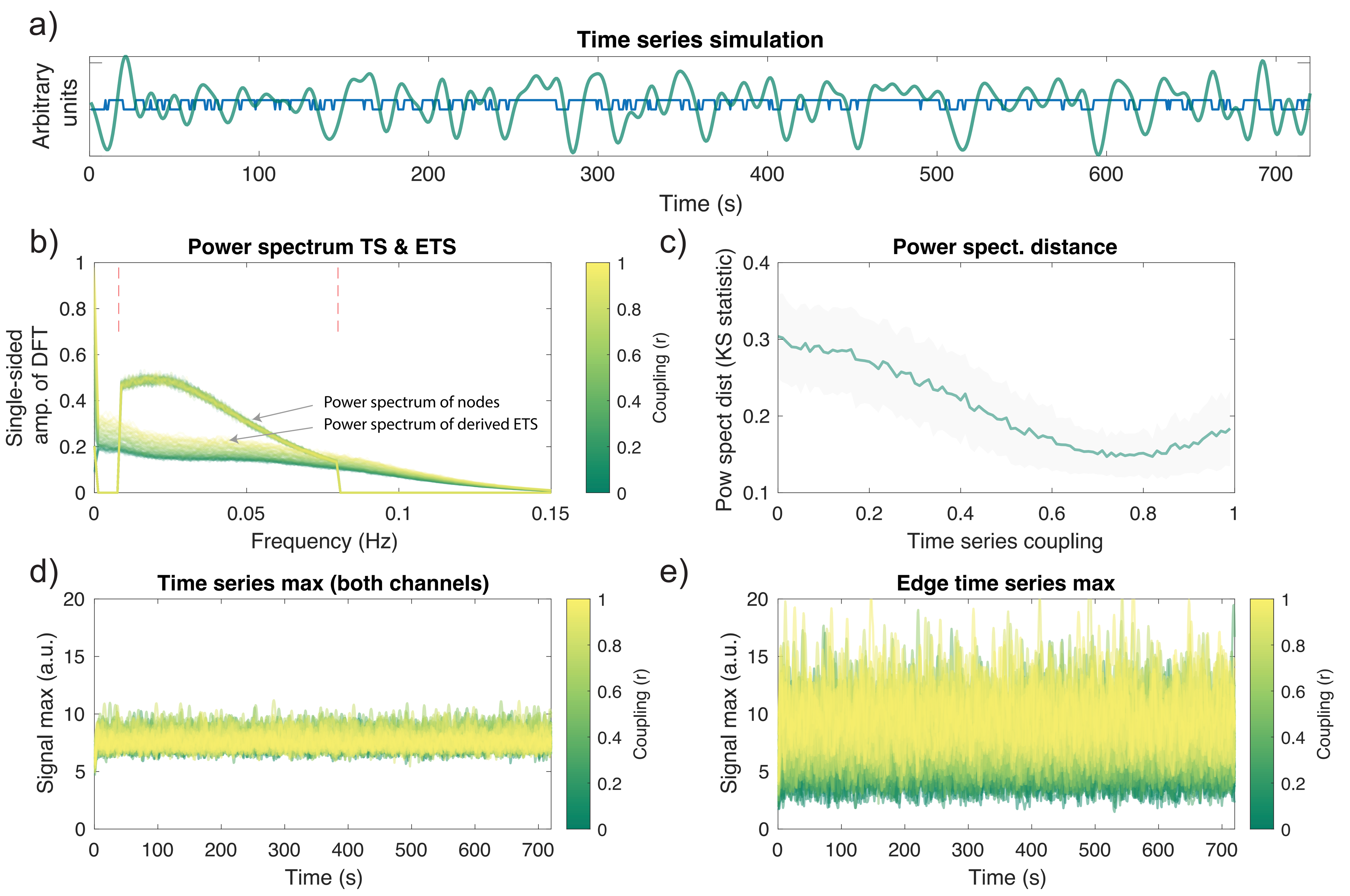
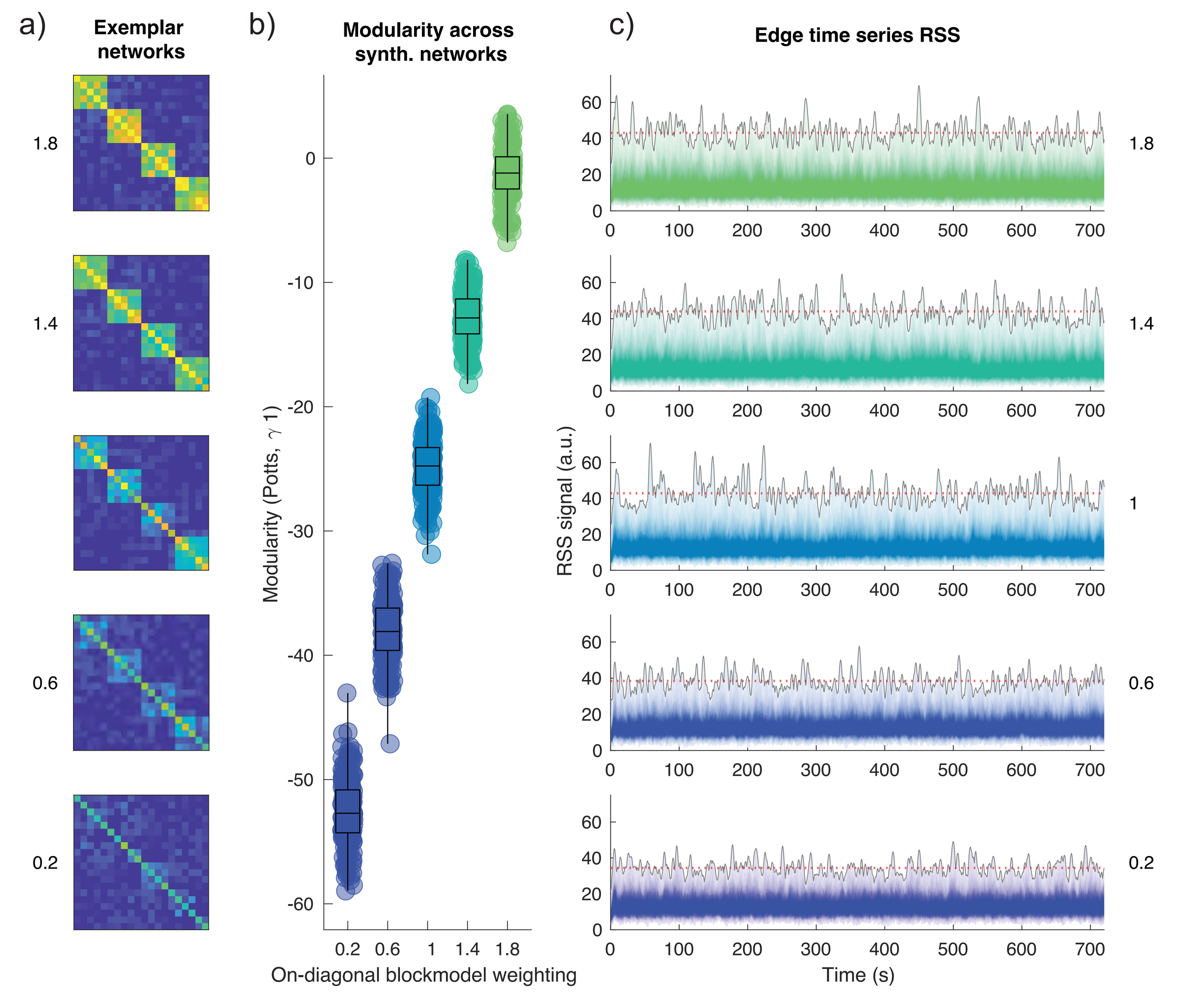


Figure 1. Using simulated data with parameterized coupling, we observe relationship between the similarity of node time series and the amplitude of edge time series. a) Example time series simulation for one channel using two-state Markov chain (blue) that is subsequently convolved with the HRF and bandpass filtered (green); 1000 time points generated b) Individual channels (n=200) adhere to bandpass filter (vertical red lines), whereas the ETS generation induces higher/lower amplitudes c) The distance (Kolmogorov-Smirnov) between node and ETS power spectra is systematically modulated by coupling of two channels, with min. around 0.8 d) Maximum values of time series within a narrow range compared to (e), the maximum values of ETS; coupling values derived from 200 simulations at each of 100 coupling values (0–.99, 0.01 steps), denoted by green-yellow color map

Figure 2. By generating a toy system of 20 node time series with a planted covariance structure, we observe that modularity affects the maximum edge time series amplitude. a) Example matrices produced by the stochastic blockmodel, at different concentrations, which result in different modularity values (b) based on Potts model with a gamma of 1. c) After generating 200 synthetic matrices, time series, and subsequently edge time series for each network, the room-sum-square (RSS) of the edge time series are taken; more extreme RSS produced, as indicated by the red line, by more modular structures, as predicted and expected based on previous studies[13,14] which discussed dependency of "events" on modularity or a relatively large leading eigenvector of the covariance matrix; max RSS: grey line, mean of max RSS: red dotted line



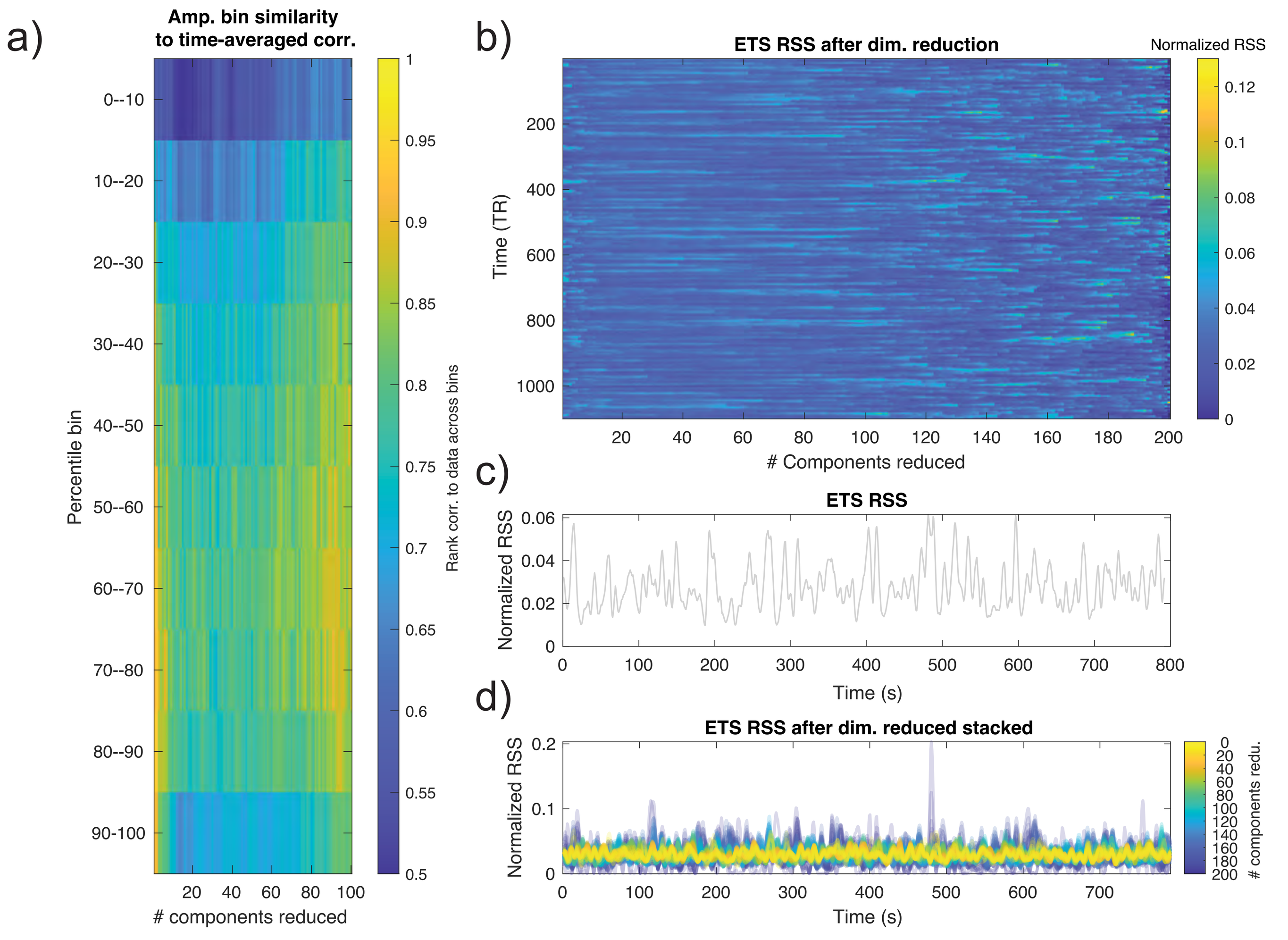


Figure 3. After increasing amount of principle components removed from time series data, binning patterns and RSS ETS change. a) RSS % bins were used demarcate data to construct 10 matrices & each matrix was compared to time-averaged connectivity, at each level of components removed b) ETS RSS as a matrix, showing how pattern of high amplitude events changes as function of variance removed c) Unperturbed ETS RSS d) Normalized ETS RSS at varying levels of perturbation, distinguished by color map; because generating ETS involves z-scoring, data with many components removed (>100) produce similar RSS magnitude as less perturbed, yet more noisy.

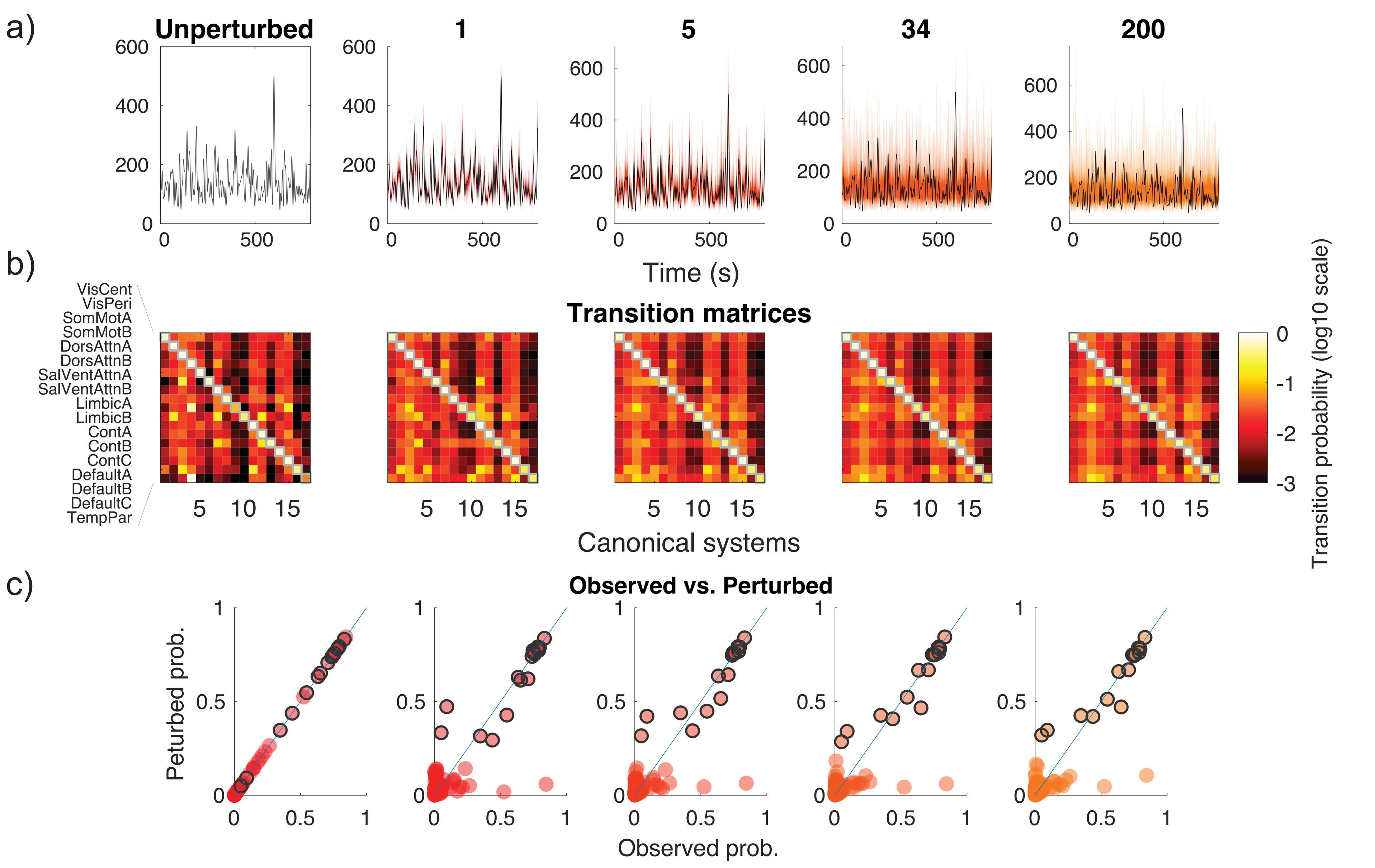


Figure 4. Applying randomization that preserves static covariance can still change edge time series phenomena. a) ETS RSS time series from an HCP resting-state scan, with varying levels of randomization applied (100 surrogate time series, as colored lines), according to the number of probabilistically sampled frequencies that were phase-shifted[8]; shift applied to all channels equally, maintaining original covariance pattern b) Transition probability matrices[7] derived from ETS and surrogate data; based on t and t+1 transitions for each node, where affiliation is dictated by max. ETS magnitude at each time point c) Original vs. surrogate data transition probability values compared, demonstrating that even a slight perturbation to data, with time-averaged covariance held constant, causing between-system changes; suggests target for future ETS applications, not tethered to time-averaged covariance.

Discussion

- Here we probe time series and edge time series characteristics, to obtain a better understanding of how their features are related. We illustrate:
  - ETS do not respect bandpass filter of original data (Fig1b), and the similarity of time series modulates the magnitude of ETS (Fig1c-e); implicates role of correlation for high amplitude ETS
  - Higher modularity of a simulated system results in higher amplitude ETS RSS (Fig. 2)
  - Similarity of ETS RSS binned data to time-averaged data holds for intact data (Fig3), and relationship is diminished after removing variance via incomplete PCA reconstructions
  - Small perturbations to time series (Fig 4a) results in large dynamics changes (Fig4b,c), even if time-averaged covariance is kept constant by the randomization method
- Indeed, some features of the time series are sufficient to estimate ETS properties[13]—notably those ETS properties that collapse across time, such as edge community similarity[3] or the distribution of high-amplitude events into specific bins[9].
  - Suggests that future work on edge time series should explore dynamics using the fine-grained precision that ETS can offer; opportunity for state-based analyses[6,7]
  - Additional line of research will focus on comprehensively characterizing ETS channel properties (power/frequency, duty cycle, burstiness) to potentially distinguish if correlation appears different, for different functional relationships; i.e., investigating different fluctuation regimes across brain.

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Checkout github.com/faskowit/ohbm23 for example code in MATLAB