Full title: Brain structural connectivity predicts brain functional complexity: DTI derived centrality accounts for variance in fractal properties of fMRI signal

Short title: Brain structural connectivity predicts brain functional complexity

Josh Neudorf (josh.neudorf@usask.ca), Chelsea Ekstrand (chelsea.ekstrand@usassk.ca), Shaylyn Kress (s.kress@usask.ca), & Ron Borowsky(ron.borowsky@usask.ca)

Cognitive Neuroscience Lab, Department of Psychology, University of Saskatchewan, 9 Campus Dr., Saskatoon, SK, Canada, S7N 5A5

Correspondence to: Ron Borowsky, Department of Psychology, University of Saskatchewan, Saskatoon, Saskatchewan, Canada, S7N 5A5.

Abstract

The complexity of brain activity has recently been investigated using the Hurst (H) exponent, which describes the extent to which functional magnetic resonance imaging (fMRI) blood oxygen-level dependent (BOLD) activity is self-similar vs. complex. For example, research has demonstrated that fMRI activity is more complex before than after consumption of alcohol (Weber et al., 2014) and during task than resting state (He, 2011). The measurement of H in fMRI is a novel method that requires the investigation of additional factors contributing to complexity. Graph theory metrics of centrality can assess how centrally important to the brain network each region is, based on diffusion tensor imaging (DTI) counts of probabilistic white matter (WM) tracts. DTI derived centrality was hypothesized to account for the complexity of functional activity, based on the supposition that more sources of information to integrate should result in more complex activity. FMRI BOLD complexity as measured by H was associated with five brain region centrality measures: degree, eigenvector, PageRank, current flow betweenness, and current flow closeness centrality. Multiple regression analyses demonstrated that degree centrality was the most robust predictor of complexity, whereby greater centrality was associated with increased complexity (lower H). Regions known to be highly connected, including the thalamus and hippocampus, notably were among the highest in centrality and complexity. This research has led to a greater understanding of the meaning of the novel Hurst exponent approach to assessing brain activity complexity, and implications for future research that employ these measures are discussed.

Keywords: fractal analysis, Hurst exponent, complexity, Graph Theory centrality, fMRI, DTI

Author Summary

Functional magnetic resonance imaging brain activity is used to calculate a measure of complexity, the Hurst exponent, which has been related to complex cognitive states in past research. For example, when engaged in cognitively demanding tasks brain activity is more complex than when no task is given, and brain activity is more complex when sober than when under the influence of alcohol. We investigated whether patterns of connections between regions in the brain may be related to baseline differences in the complexity of fMRI brain activity between different brain regions. Diffusion tensor imaging allowed us to estimate the number of connections between regions of the brain, and Graph theory allowed us to describe these patterns of connections in the brain. We found that the graph theory metric of *degree centrality* (the number of connections to a region) is able to most robustly predict how complex the brain activity is, suggesting that the Hurst exponent complexity measure is sensitive to integration of information from multiple sources. Our findings represent important progress towards understanding the biological bases of signal complexity in the brain, and exemplifies how structural connectivity centrality can predict brain function complexity.

Brain structural connectivity predicts brain functional complexity:

DTI derived centrality accounts for variance in fractal properties of fMRI signal

1. Introduction

Neuroimaging analyses have evolved since the advent of techniques such as functional magnetic resonance imaging (fMRI) to better understand what the blood oxygen level dependent (BOLD) signal implies about the underlying processing in the brain. For example, analyses have improved from a simple average of BOLD level during task vs. rest, to modeling expected activation time course based on an empirically derived hemodynamic response function convolved with the time course of stimuli presentations. Furthermore, resting state fMRI studies have revealed interesting baseline patterns of activation (i.e., resting state networks), and ushered in an age of network science in brain research. With the rise in resting state fMRI research, predicting resting state fMRI functional connectivity from diffusion tensor imaging (DTI) structural connectivity has been an important recent endeavor for researchers, and the use of graph theory analyses of structural networks have been integral to these investigations (e.g., [1,2,3,4,5]). Furthermore, there has been recent interest in predicting task-based fMRI activation from DTI structural connectivity [6]. An important next-step is to explore the extent to which one can predict the complexity in fMRI activation from the underlying DTI structure.

Since early demonstrations of using the Hurst exponent from the toolbox of chaos theory and fractals to analyse fMRI BOLD signal complexity (e.g., [7,8,9]), interest has grown in this novel method for characterizing complexity of fMRI activation. The Hurst exponent has been applied to many domains of research including Alzheimer's disease [10], signal complexity change over the adult lifespan [11], distress related to medical treatment [12], task versus rest states [13], and alcohol-induced intoxication versus non-intoxicated states [14]. Other measures

of complexity such as functional variability have also demonstrated meaningful real-world associations (e.g., children develop more complex brain activity with age, see [15]). In the present research we apply network science graph theory metrics of *centrality* (i.e., how centrally important a particular region is to the network) as a novel way to further explore this important application of fractal analysis for characterising fMRI activation complexity.

1.1 Fractal Analysis of FMRI BOLD Signal Complexity

Fractal analysis of time course data measures the self-similarity or autocorrelation of the signal over different scales. High autocorrelation signifies a "long-memory" process that is similar over shorter and longer time scales, whereas low autocorrelation signifies a "short-memory" process that varies between shorter and longer time scales. Complexity can be used as a descriptive analogous concept relating to these measures, whereby high autocorrelation (long-memory process) is less complex than low autocorrelation (short-memory process). The Hurst exponent (H) is one method of measuring signal complexity with fractal analysis, and describes the extent to which time course data such as fMRI BOLD signal activity is self-similar (H closer to 1) vs. complex (H closer to 0.5).

The complexity of brain activity has recently been investigated using H. Previous research has demonstrated that fMRI activity is more complex before consumption of alcohol than after consumption of alcohol [14] and more complex during task than resting state [13]. Aging has been associated with a reorganization of complexity, with left parietal and frontal regions losing complexity with age, while increases in complexity with age were observed in the insula, limbic system, and temporal lobe [11]. Alzheimer's disease has been associated with lower complexity than healthy controls in regions of the brain including medial and lateral temporal cortex, dorsal cingulate cortex, premotor cortex, left precentral gyrus, and left

postcentral gyrus [10]. The measurement of H in resting state and task fMRI is a novel method that requires the investigation of additional factors contributing to BOLD signal complexity. One possible factor to be investigated is the connective structure of the brain network, which should play a vital role in determining the intrinsic patterns of coactivation of brain regions.

1.2 Graph Theory Analysis of Brain Network Centrality

Graph theory analyses of networks such as the diffusion tensor imaging (DTI) structural connectivity network of the brain allow for assessment of how centrally important to the network a particular region is, via calculation of that region's centrality. The most basic example of centrality is *degree centrality*, which is the count of connections between all other regions in the network to the region of interest. Other methods of calculating centrality represent more specific features of how centrally important to the network that regions is, such as weighting connections to the region based on how connected each other region is (*eigenvector centrality*; [16]), a method conceptually similar to eigenvector centrality that adjusts for the biased effect of largely connected regions on regions with low connections (*PageRank centrality*; [17]), counting the number of shortest paths between two regions in the network that pass through the region of interest (*betweenness centrality*; [18,19]), and average shortest path distance from the region to each other region in the network (*closeness centrality*; [20]). Variants based on current flow for betweenness centrality (*current flow betweenness centrality*; [21]) and closeness centrality (*current flow closeness centrality*; [21,22]) capture similar features while using an electrical current model for information spreading, which may be more applicable to brain activity. Closeness and betweenness centrality are particularly sensitive to the topological role of a region in routing information between regions along shortest paths, and less sensitive to the number of connections. Graph theory centrality metrics allow for assessing specific ways that information is

integrated and communicated through regions in the brain network (see [23] for a description of these methods).

1.3 Relating Complexity to Centrality

Task vs. rest [13] and sober vs. intoxicated [14] states have been used to show that BOLD activity is more complex as measured by H during more organized cognitive states. Sufficient understanding has not yet been reached as to the reasons for increased complexity during these states, and one possibility is that this increased complexity during organized brain processing may be due to integrated co-processing of information from various brain regions concurrently. If this is the case, then regardless of task, regions that are more highly integrated via white matter (WM) tract connections to the rest of the brain network should have more complex activity than regions that are less connected to other brain regions, as these regions would be integrating information from more sources than other regions. The current research tests the hypothesis that DTI structural connectivity derived centrality measures sensitive to integration from many sources should be able to account for variation in the complexity of functional activity, based on the supposition that more sources of information to integrate should result in more complex activity.

2. Results

Mean H was used as the criterion variable in simple and multiple linear regression models with centrality measures as predictor variables. For the simple regression models, degree centrality ($\beta = -2.369 \times 10^{-4}$, $t(266) = -5.879$, $p < .001$, $R^2 = .112$; see Fig 1A), eigenvector centrality ($\beta = -2.335 \times 10^{-4}$, $t(266) = -5.782$, $p < .001$, $R^2 = .108$; see Fig 1B), and PageRank centrality ($\beta = -2.333 \times 10^{-4}$, $t(266) = -5.778$, $p < .001$, $R^2 = .108$; see Fig 1C) were found to be negatively associated with H, while current flow closeness centrality ($\beta = 1.451 \times 10^{-4}$, $t(266) =$

3.372, $p < .001$, $R^2 = .037$; see Fig 1D), and log transformed approximate current flow betweenness centrality ($\beta = 2.368 \times 10^{-4}$, $t(266) = 3.178$, $p = .002$, $R^2 = .033$; see Fig 1E) were found to be positively associated with H (see Fig 1 for scatterplots of Hurst exponent as a function of centrality). In these linear regression models current flow closeness centrality and approximate current flow betweenness centrality are positively associated with H, likely owing to their particular sensitivity to their position along shortest paths and distance from other regions, which measures routing rather than integration.

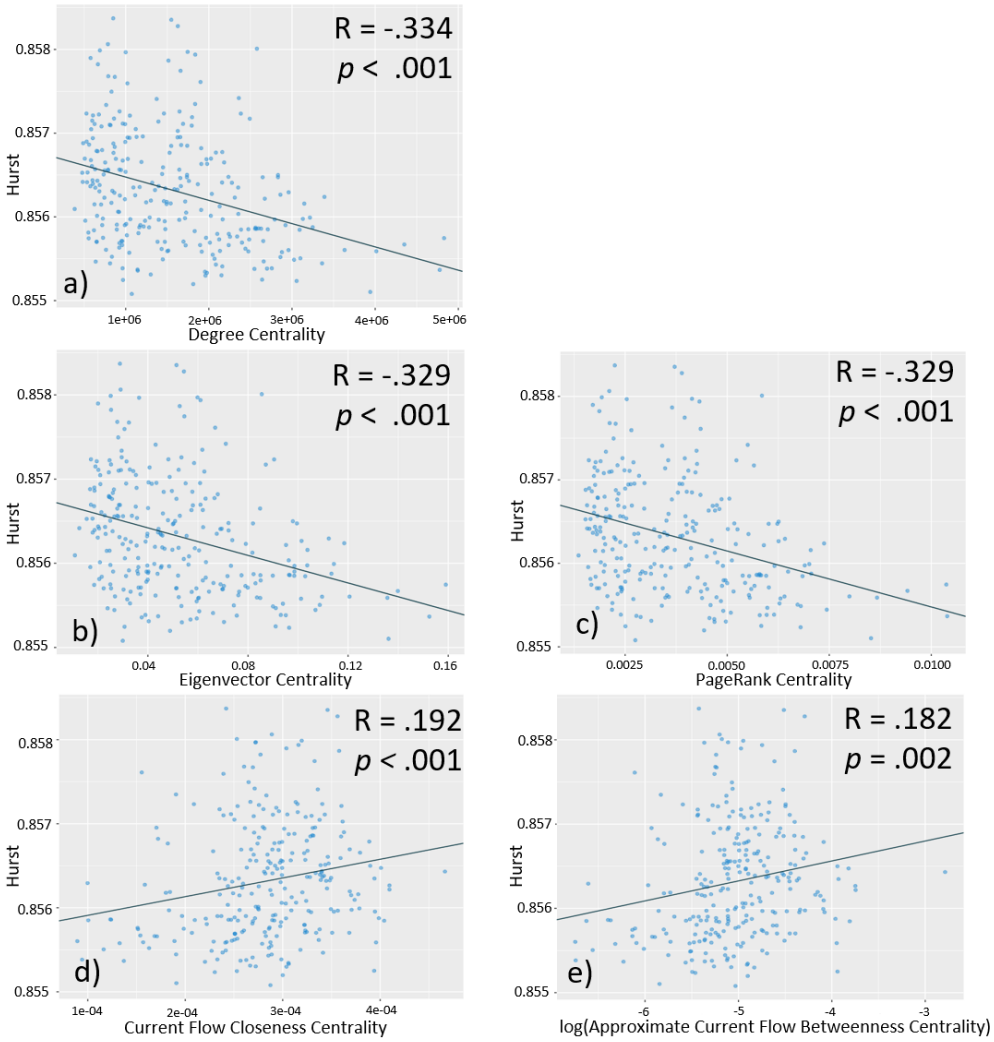

Fig 1. Scatterplots of Hurst exponent as a function of centrality. Centrality measures used are: a) degree centrality, b) eigenvector centrality, c) PageRank centrality, d) current flow closeness centrality, and e) approximate current flow betweenness centrality.

Considering the high amount of collinearity between degree centrality, eigenvector centrality, and PageRank centrality, and also between current flow closeness centrality and log approximate betweenness centrality (see Table 1), these predictor variables were not included in the same multiple linear regression. Including degree centrality with current flow closeness centrality in a multiple linear regression model, there was a negative effect of degree centrality ($\beta = -2.144\times 10^{-4}$, $t(266) = -4.904$, $p < .001$), while current flow closeness centrality ($\beta = 5.771\times 10^{-5}$, $t(266) = 1.320$, $p = .188$) was not significant in this model ($R^2 = .114$, $F(2,265 = 18.20)$, $p < .001$). Including degree centrality with log approximate current flow closeness centrality in a multiple linear regression model, there was a negative effect of degree centrality ($\beta = -2.163\times 10^{-4}$, $t(266) = -5.107$, $p < .001$), while log approximate current flow betweenness centrality ($\beta = 6.552\times 10^{-5}$, $t(266) = 1.547$, $p = .123$) was not significant in this model ($R^2 = .116$, $F(2,265 = 18.57)$, $p < .001$). Analogous models including eigenvector or PageRank centrality in place of degree centrality yield the same pattern of results, but the models with degree centrality consistently accounted for the most variance. These models demonstrated that the current flow centrality metrics do not account for a significant amount of variance when included in a multiple linear regression model with either degree centrality, eigenvector centrality, or PageRank centrality, and that the negative association between centrality and H is robust, whereby higher degree, eigenvector, and PageRank centrality is associated with lower H (higher complexity). Consistently in each of the degree centrality, eigenvector centrality, and PageRank centrality models, examples of the highest centrality regions, which also had some of the lowest values of H (highest complexity), included the left and right anterior and posterior regions of the thalamus (well-known to be important for connecting regions related to various different modalities), and regions of the medial temporal gyrus including the right posterior hippocampus

(commonly viewed as being integral in the encoding of multi-modal information from many disparate brain regions, e.g., [24]; see also [25] for a review; see Fig 2 for example sagittal and axial brain slices of degree centrality and H in various regions including the thalamus and hippocampus).

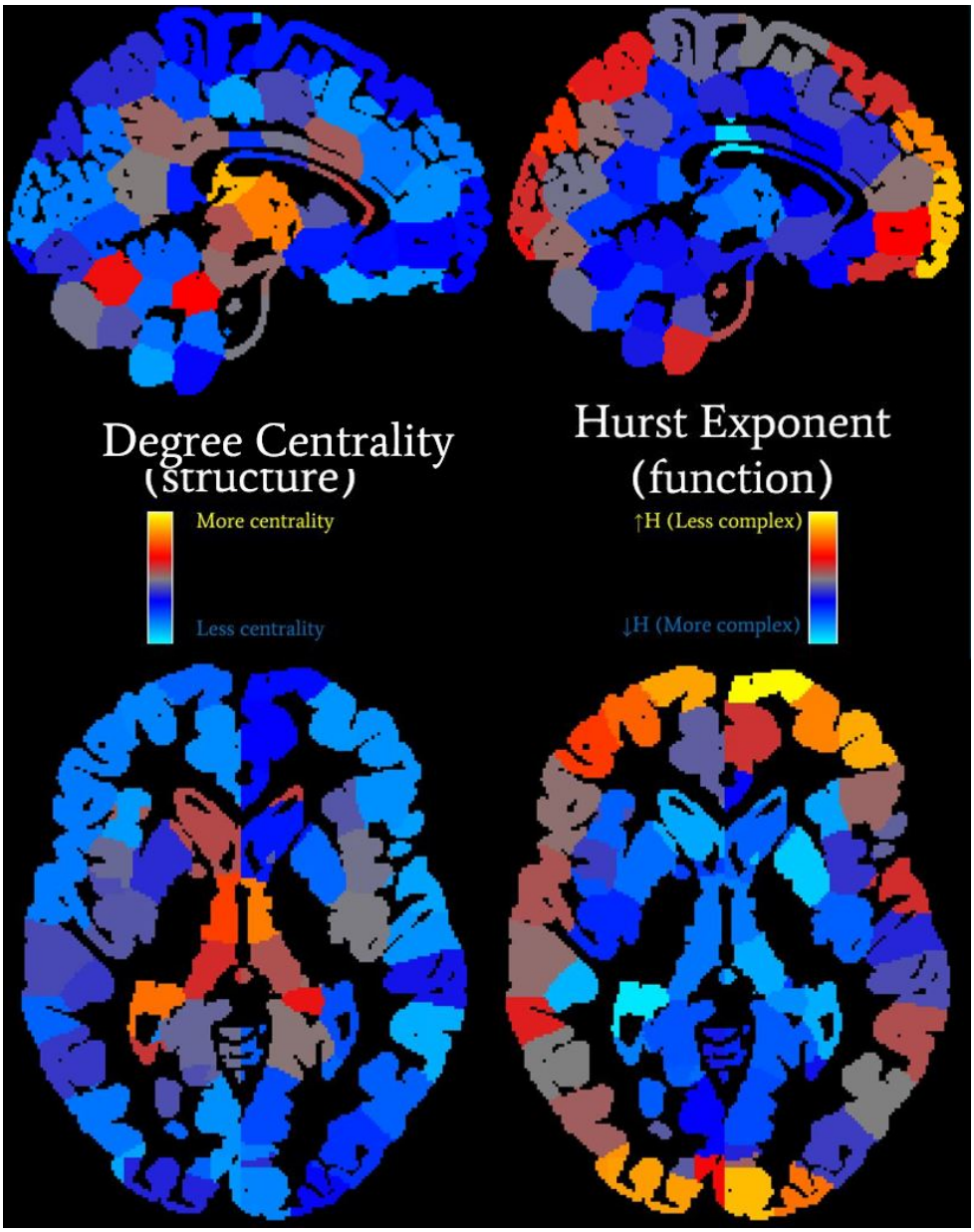

Fig 2. Example brain maps of degree centrality (left) and Hurst exponent (right), where yellow indicates higher values and blue indicates lower values. Centrality tended to be negatively associated with H, such that higher centrality (greater central importance to the network) was associated with lower H (more complexity).

Table 1. Predictor variable correlation matrix to assess multicollinearity. Values represent Pearson's R correlation. Asterisks denote high collinearity (*R* > .95).

	Degree	Eigenvector	PageRank	Closeness	log(Betweenness)	Hurst
Degree	1	.985*	.999*	-.391	-.315	-.339
Eigenvector		1	.978*	-.416	-.343	-.334
PageRank			1	-.380	-.304	-.334
Closeness				1	.979*	.202
log(Betweenness)					1	.191
Hurst						1

3. Discussion

Fractal analysis of fMRI activity is a recent technique demonstrating that lower H is related to higher complexity of cognitive processing (e.g., [10,13,14]). Our research demonstrated that higher complexity fMRI activity (lower H) can be explained in part by the centrality of the region in the structural DTI connectivity network. Specifically, degree centrality, eigenvector centrality, and PageRank centrality were negatively associated with H, meaning higher centrality on these measures produced more complex functional activity (lower H). Conversely, current flow closeness centrality and approximate current flow betweenness centrality were positively associated with H, suggesting that these metrics are associated with less complex activation because they are particularly sensitive to simple routing of information rather than integration of information from many sources. Overall, in both simple and multiple regression analyses, degree centrality consistently showed the strongest negative relationship with H (positive relationship with complexity), and as such may be the most robust metric of centrality to use in the future when associating DTI structural connectivity to resting state fMRI

BOLD activity. Conversely, the interesting positive relationship with H demonstrated by current flow closeness centrality and approximate current flow betweenness centrality was not robust, as it was not significant in the multiple regression model. The positive relationship between these current flow centrality metrics and H is likely related to the sensitivity of these regions to topological location along shortest paths, which facilitate communication between distant regions in the network. In general, increased complexity with increased degree centrality suggests that the complexity of fMRI BOLD activation increases in the presence of integration of information from many sources.

3.1 Implications

With this evidence that complexity measured by H is related to centrality in the network, baseline expectations for complexity could be assessed at the level of each brain region using DTI structural connectivity networks before assessing task-based differences in fMRI complexity. Task fMRI data could also be examined with respect to complexity measured with H, as an indicator of information integration during tasks that manipulate integration of multiple modalities of information, such as semantic processing involving integration of action, shape, colour, emotional, and auditory modalities. Amodal semantic hubs hypothesized to be involved in integration of multiple modalities (e.g., the anterior temporal lobe; see [26,27]) may have higher complexity as measured by H than modal regions focused on a single modality (e.g., action, shape, colour, etc.) during semantic tasks, and other potential integrative hubs may also be identified in this way. Additionally, this knowledge of the relation of structural connectivity patterns to fMRI signal complexity could help to investigate reorganization of brain signal complexity with age from the lens of comorbid structural connectivity reorganization (see [11]).

3.2 Conclusions

The investigation of the fractal indicator, H, of complexity and its relation to DTI structural network dynamics via graph theory centrality analyses undertaken in this research has demonstrated inherent differences in the complexity of fMRI BOLD signals can be accounted for by structural connectivity centrality of the various regions in the brain. This finding suggests that complexity is dependant not just on task (e.g., [13]) or on biological state (e.g., [14]), but also on the structural pattern of the connections as studied through graph theory analysis of DTI probabilistic streamlines. Supporting the validity of our approach, regions known to be highly connected, including the thalamus and hippocampus, were among the highest in centrality and complexity. The number of connections to other regions in the brain (degree centrality) is positively and consistently related to the complexity of brain activity as measured with fMRI. This research contributes to a greater understanding of the novel use of the Hurst exponent in assessing complexity of fMRI BOLD signals.

4. Materials and Methods

High quality DTI and resting state fMRI data for 100 unrelated subjects were obtained from the Human Connection Project (HCP) database ([28]; please see [28] for ethics statements). The HCP resting state fMRI data was used, which has been FSL *FIX* [29] preprocessed, white matter and cerebrospinal fluid activation regressed, and has undergone non-linear registration to Montreal Neurological Institute (MNI) standard space. All four sessions of this resting state fMRI data from HCP (4 sessions of 1200 acquisitions each, totalling 58 minutes) were used to calculate H for each voxel using a discrete wavelet transform approximation method with a Haar mother wavelet (e.g., see [30]) in Python (Python Software Foundation,

https://www.python.org). Mean H of the 4 sessions was calculated for each voxel, and then mean H was calculated for each of the 268 regions from the Shen functional atlas [31].

Probabilistic tractography was performed on the DTI data using FSL's GPU implementation of *probtrackX* [32,33] with a NVIDIA GTX 1080 graphics card, and the streamline pathway length correction option was applied. Importantly, the GPU implementation of *probtrackX* allowed for the computation of the 268 region connectivity matrix for more than one participant per day, allowing us to complete the calculations in approximately 3 months, whereas the default CPU implementation would have taken more than a week for each participant with the HCP high resolution DTI data (1.25mm x 1.25mm x 1.25mm resolution, 90 directions), which would have led to over 2 years of computation time. Probabilistic tractography is much more computationally intensive than deterministic tractography, and as such this resulting data represents an important contribution to the field of brain connectome research. The probabilistic tractography produced asymmetric structural connectivity matrices, which were converted to symmetric matrices by calculating the maximum streamline count between the cell in row *i* column *j*, and the cell in row *j* column *i*. The connectivity matrix was then used to compute streamline weighted graph theory centrality measures of: 1) degree centrality (total connections to the region); 2) eigenvector centrality (number of connections weighted by degree of the connected region); 3) PageRank centrality (computes a ranking of the nodes based on the structure of the incoming links, originally designed as an algorithm to rank web pages; computed with α equal to the default of 0.85); 4) current flow closeness centrality (current flow method based on mean connectivity distance to other regions); and 5) approximate current flow betweenness centrality (current flow method based on the number shortest paths the region is on). These graph theory metrics were calculated using the *NetworkX* python library, and the

definitions provided are informed by the *NetworkX* documentation [34]. The reciprocal of the DTI connectivity matrix was calculated and used as the weights for the current flow closeness centrality and approximate current flow betweenness centrality, as these models determine shortest paths assuming that edge weights represent effective resistance in that path.

The means for H and degree centrality metrics were computed across participants so that a mean value was assigned to each of the 268 brain regions. Mean H was then modeled as the criterion variable in a linear regression with centrality metrics as predictors. H was regressed on each of these centrality metrics separately and then multiple regression models were examined to investigate shared variance between the centrality metrics. The data that support the findings of this study are openly available in Zenodo at https://doi.org/10.5281/zenodo.3509709 [35].

REFERENCES

1. Honey CJ, Thivierge J-P, Sporns O. Can structure predict function in the human brain? NeuroImage. 2010;52: 766–776. doi:10.1016/j.neuroimage.2010.01.071

2. Goñi J, van den Heuvel MP, Avena-Koenigsberger A, Velez de Mendizabal N, Betzel RF, Griffa A, et al. Resting-brain functional connectivity predicted by analytic measures of network communication. Proc Natl Acad Sci U S A. 2014;111: 833–838. doi:10.1073/pnas.1315529111

3. Bettinardi RG, Deco G, Karlaftis VM, Van Hartevelt TJ, Fernandes HM, Kourtzi Z, et al. How structure sculpts function: Unveiling the contribution of anatomical connectivity to the brain's spontaneous correlation structure. Chaos. 2017;27: 047409. doi:10.1063/1.4980099

4. Zhang R, Shao R, Xu G, Lu W, Zheng W, Miao Q, et al. Aberrant brain structural–functional connectivity coupling in euthymic bipolar disorder. Human Brain Mapping. 2019;40: 3452–3463. doi:10.1002/hbm.24608

5. Chen Z, Hu X, Chen Q, Feng T. Altered structural and functional brain network overall organization predict human intertemporal decision-making. Human Brain Mapping. 2019;40: 306–328. doi:10.1002/hbm.24374

6. Osher DE, Saxe RR, Koldewyn K, Gabrieli JDE, Kanwisher N, Saygin ZM. Structural Connectivity Fingerprints Predict Cortical Selectivity for Multiple Visual Categories across Cortex. Cereb Cortex. 2016;26: 1668–1683. doi:10.1093/cercor/bhu303

7. Bullmore E, Long C, Suckling J, Fadili J, Calvert G, Zelaya F, et al. Colored noise and computational inference in neurophysiological (fMRI) time series analysis: Resampling methods in time and wavelet domains. Human Brain Mapping. 2001;12: 61–78. doi:10.1002/1097-0193(200102)12:2<61::AID-HBM1004>3.0.CO;2-W

8. Fadili MJ, BuIlmore ET, Breatt M. Wavelet methods for characterising mono- and poly-fractal noise structures in shortish fMRI time series. NeuroImage. 2001;13: 116. doi:10.1016/S1053-8119(01)91459-4

9. Shimizu Y, Barth M, Windischberger C, Moser E, Thurner S. Wavelet-based multifractal analysis of fMRI time series. NeuroImage. 2004;22: 1195–1202. doi:10.1016/j.neuroimage.2004.03.007

10. Maxim V, Şendur L, Fadili J, Suckling J, Gould R, Howard R, et al. Fractional Gaussian noise, functional MRI and Alzheimer's disease. NeuroImage. 2005;25: 141–158. doi:10.1016/j.neuroimage.2004.10.044

11. Dong J, Jing B, Ma X, Liu H, Mo X, Li H. Hurst Exponent Analysis of Resting-State fMRI Signal Complexity across the Adult Lifespan. Front Neurosci. 2018;12. doi:10.3389/fnins.2018.00034

12. Churchill NW, Cimprich B, Askren MK, Reuter-Lorenz PA, Jung MS, Peltier S, et al. Scale-free brain dynamics under physical and psychological distress: Pre-treatment effects in women diagnosed with breast cancer. Human Brain Mapping. 2015;36: 1077–1092. doi:10.1002/hbm.22687

13. He BJ. Scale-Free Properties of the Functional Magnetic Resonance Imaging Signal during Rest and Task. J Neurosci. 2011;31: 13786–13795. doi:10.1523/JNEUROSCI.2111-11.2011

14. Weber AM, Soreni N, Noseworthy MD. A preliminary study on the effects of acute ethanol ingestion on default mode network and temporal fractal properties of the brain. Magn Reson Mater Phy. 2014;27: 291–301. doi:10.1007/s10334-013-0420-5

15. McIntosh AR, Kovacevic N, Itier RJ. Increased Brain Signal Variability Accompanies Lower Behavioral Variability in Development. PLOS Computational Biology. 2008;4: e1000106. doi:10.1371/journal.pcbi.1000106

16. Bonacich P. Power and Centrality: A Family of Measures. American Journal of Sociology. 1987;92: 1170–1182. doi:10.1086/228631

17. Page L, Brin S, Motwani R, Winograd T. The PageRank Citation Ranking: Bringing Order to the Web. 11 Nov 1999 [cited 23 Sep 2019]. Available: http://ilpubs.stanford.edu:8090/422/

18. Anthonisse JM. The rush in a directed graph. Stichting Mathematisch Centrum; 1971. Available: https://ir.cwi.nl/pub/9791

19. Freeman LC. A set of measures of centrality based on betweenness. Sociometry. 1977;40: 35-41.

20. Bavelas A. Communication Patterns in Task-Oriented Groups. The Journal of the Acoustical Society of America. 1950;22: 725–730. doi:10.1121/1.1906679

21. Brandes U, Fleischer D. Centrality Measures Based on Current Flow. In: Diekert V, Durand B, editors. STACS 2005. Berlin, Heidelberg: Springer Berlin Heidelberg; 2005. pp. 533–544. doi:10.1007/978-3-540-31856-9_44

22. Stephenson K, Zelen M. Rethinking centrality: Methods and examples. Social Networks. 1989;11: 1–37. doi:10.1016/0378-8733(89)90016-6

23. Rubinov M, Sporns O. Complex network measures of brain connectivity: Uses and interpretations. NeuroImage. 2010;52: 1059–1069. doi:10.1016/j.neuroimage.2009.10.003

24. Damasio AR. The Brain Binds Entities and Events by Multiregional Activation from Convergence Zones. Neural Computation. 1989;1: 123–132. doi:10.1162/neco.1989.1.1.123

25. Bird CM, Burgess N. The hippocampus and memory: insights from spatial processing. Nat Rev Neurosci. 2008;9: 182–194. doi:10.1038/nrn2335

26. Patterson K, Nestor PJ, Rogers TT. Where do you know what you know? The representation of semantic knowledge in the human brain. Nature Reviews Neuroscience. 2007;8: 976–987. doi:10.1038/nrn2277

27. Neudorf J, Ekstrand C, Kress S, Borowsky R. FMRI of shared-stream priming of lexical identification by object semantics along the ventral visual processing stream. Neuropsychologia. 2019;133: 107185. doi:10.1016/j.neuropsychologia.2019.107185

28. Van Essen DC, Smith SM, Barch DM, Behrens TEJ, Yacoub E, Ugurbil K. The WU-Minn Human Connectome Project: An overview. NeuroImage. 2013;80: 62–79. doi:10.1016/j.neuroimage.2013.05.041

29. Salimi-Khorshidi G, Douaud G, Beckmann CF, Glasser MF, Griffanti L, Smith SM. Automatic Denoising of Functional MRI Data: Combining Independent Component Analysis and Hierarchical Fusion of Classifiers. Neuroimage. 2014;90: 449–468. doi:10.1016/j.neuroimage.2013.11.046

30. Manimaran P, Panigrahi PK, Parikh JC. On Estimation of Hurst Scaling Exponent through Discrete Wavelets. arXiv:physics/0604004. 2006 [cited 17 Dec 2018]. Available: http://arxiv.org/abs/physics/0604004

31. Shen X, Tokoglu F, Papademetris X, Constable RT. Groupwise whole-brain parcellation from resting-state fMRI data for network node identification. NeuroImage. 2013;82: 403–415. doi:10.1016/j.neuroimage.2013.05.081

32. Behrens TEJ, Woolrich MW, Jenkinson M, Johansen-Berg H, Nunes RG, Clare S, et al. Characterization and propagation of uncertainty in diffusion-weighted MR imaging. Magnetic Resonance in Medicine. 2003;50: 1077–1088. doi:10.1002/mrm.10609

33. Hernandez-Fernandez M, Reguly I, Jbabdi S, Giles M, Smith S, Sotiropoulos SN. Using GPUs to accelerate computational diffusion MRI: From microstructure estimation to tractography and connectomes. NeuroImage. 2019;188: 598–615. doi:10.1016/j.neuroimage.2018.12.015

34. Hagberg AA, Schult DA, Swart PJ. Exploring Network Structure, Dynamics, and Function using NetworkX. Proceedings of the 7th Python in Science Conference. 2008; 11-16.

35. Neudorf J, Ekstrand C, Kress S, Borowsky R. Data for: Brain structural connectivity predicts brain functional complexity: DTI derived centrality accounts for variance in fractal properties of fMRI signal. Zenodo; 2019. doi:10.5281/zenodo.3509709

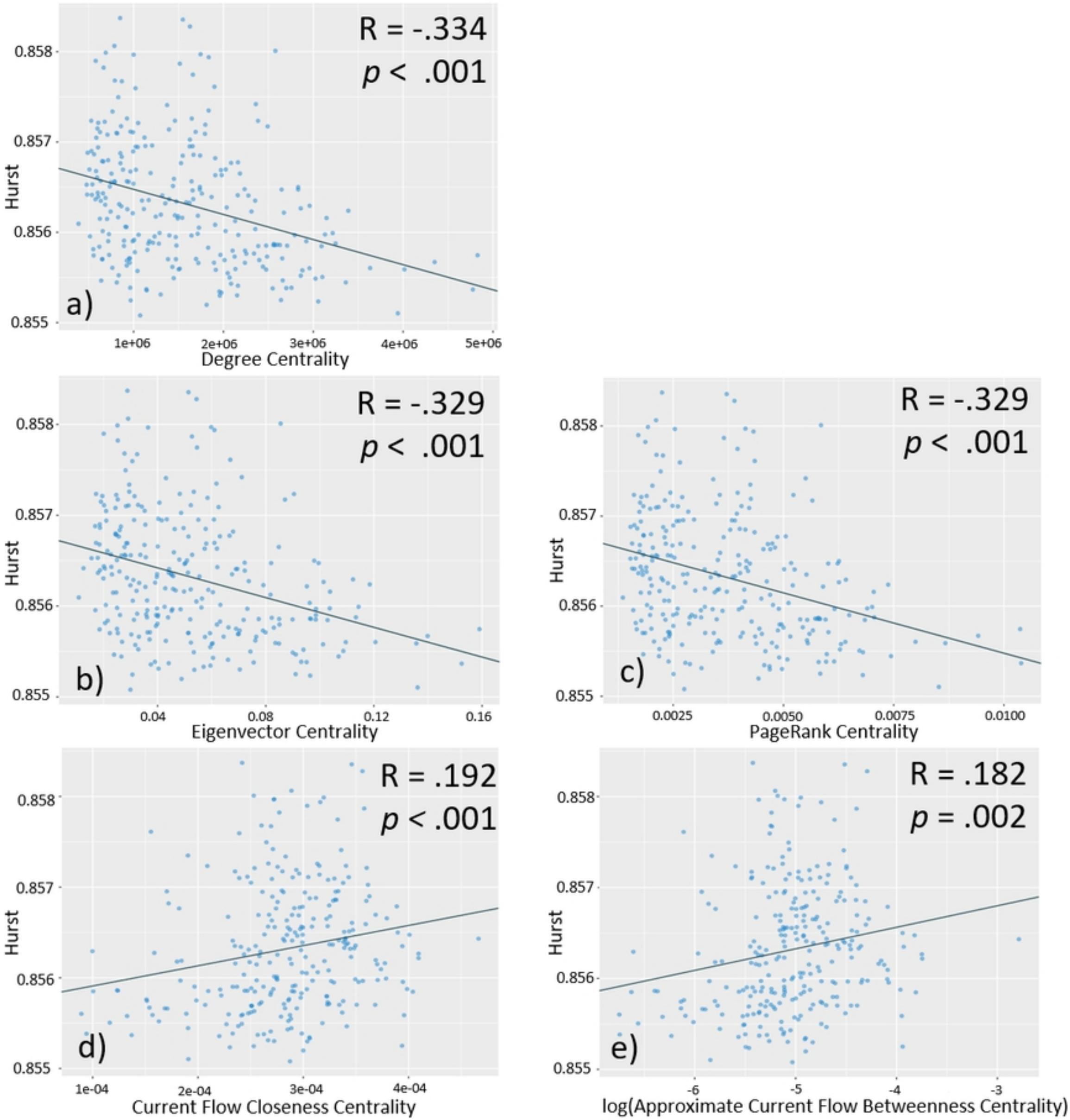
R = -.334
p < .001
a)
Hurst
Degree Centrality
R = -.329
p < .001
b)
Eigenvector Centrality
R = -.329
p < .001
c)
PageRank Centrality
R = .192
p < .001
d)
Current Flow Closeness Centrality
R = .182
p = .002
e)
log(Approximate Current Flow Betweenness Centrality)

Fig 1

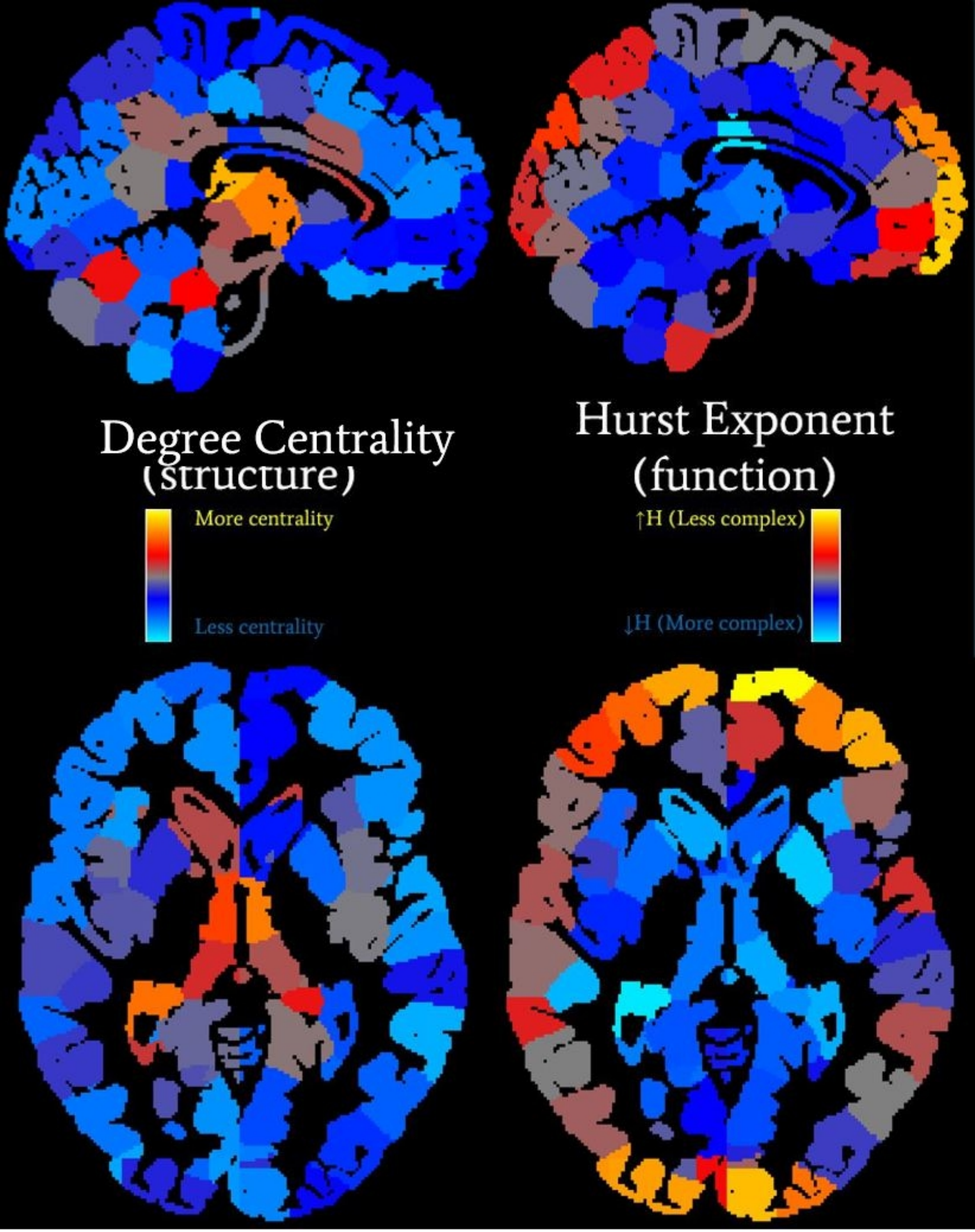
Degree Centrality
(structure)
More centrality
Less centrality
Hurst Exponent
(function)
↑H (Less complex)
↓H (More complex)

Fig 2