RSFC_parcellation_AZSnyder_OHBM2017

Different parcellation techniques give different answers

- Sulci & gyri (AAL) (Tzourio-Mazoyer et al., 2002)
- Histology (Brodmann areas)
- Gene expression (https://www.alleninstitute.org)
- Receptor density mapping (Amunts and Zilles, 2015; Zilles and Amunts, 2009)
- RSFC (Biswal et al., 1995)

What is RSFC?

- ICA vs. seed-based correlation (Beckmann et al., 2005; Fox et al., 2005; Shehzad et al., 2009)
- RSFC data quality issues
  - Artifact (Behzadi et al., 2007; Jo et al., 2010; Power et al., 2012; Power et al., 2014)
  - Quantity of RSFC data (Laumann et al., 2015)
  - State-dependence (Tagliazucchi and Laufs, 2014)
- RSFC is hierarchically organized (Cordes and Nandy, 2006; Doucet et al., 2011; Hacker et al., 2013; Lee et al., 2012)

RSFC as a parcellation tool

- Inner product-based RSN clustering (Lee et al., 2012; Yeo et al., 2011)
- Graph-theoretic parcellation (Power et al., 2011)
- Boundary mapping and parcel homogeneity evaluation (Cohen et al., 2008; Wig et al., 2014a; Wig et al., 2014b)
- RSFC parcellation consistency across studies (Gordon et al., 2016)
- Relation of RSNs to function (Smith et al., 2009; Yeo et al., 2015)
- Gradients vs. seed-mapping can yield different answers (Buckner and Yeo, 2014)
- V1-V2 Parcellation and genetics vs. experience in development (Striem-Amit et al., 2015)

Individual RSFC differences (Dubois and Adolphs, 2016)

- Individual differences in RSFC (Laumann et al., 2015; Mueller et al., 2013)
- Supervised vs. unsupervised classification (Hacker et al., 2013)

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Tools to parcellate the brain and its relation to function: Part II

Resting state functional connectivity

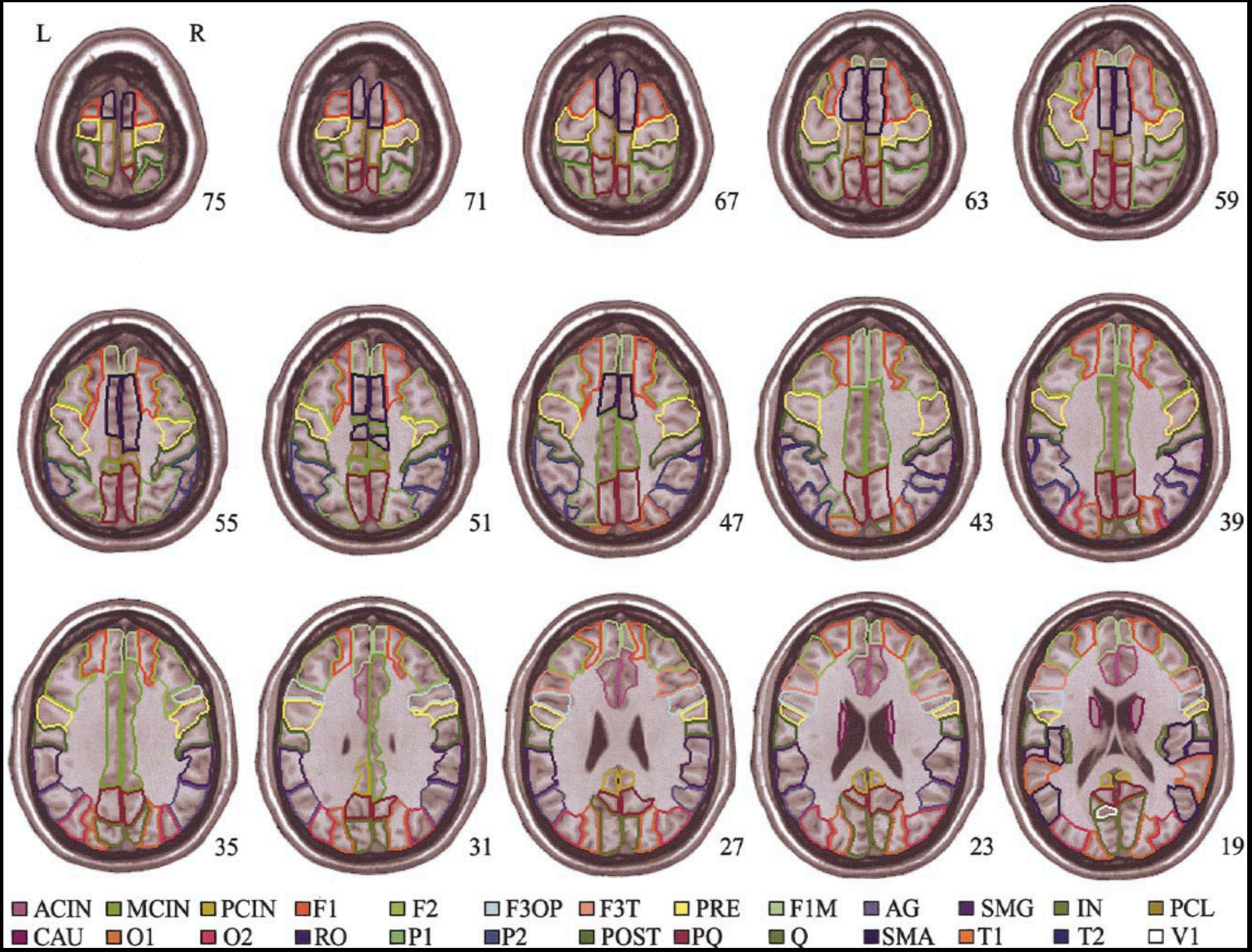
A. Z. Snyder
Washington University School of Medicine
June 25, 2017

Course Objectives

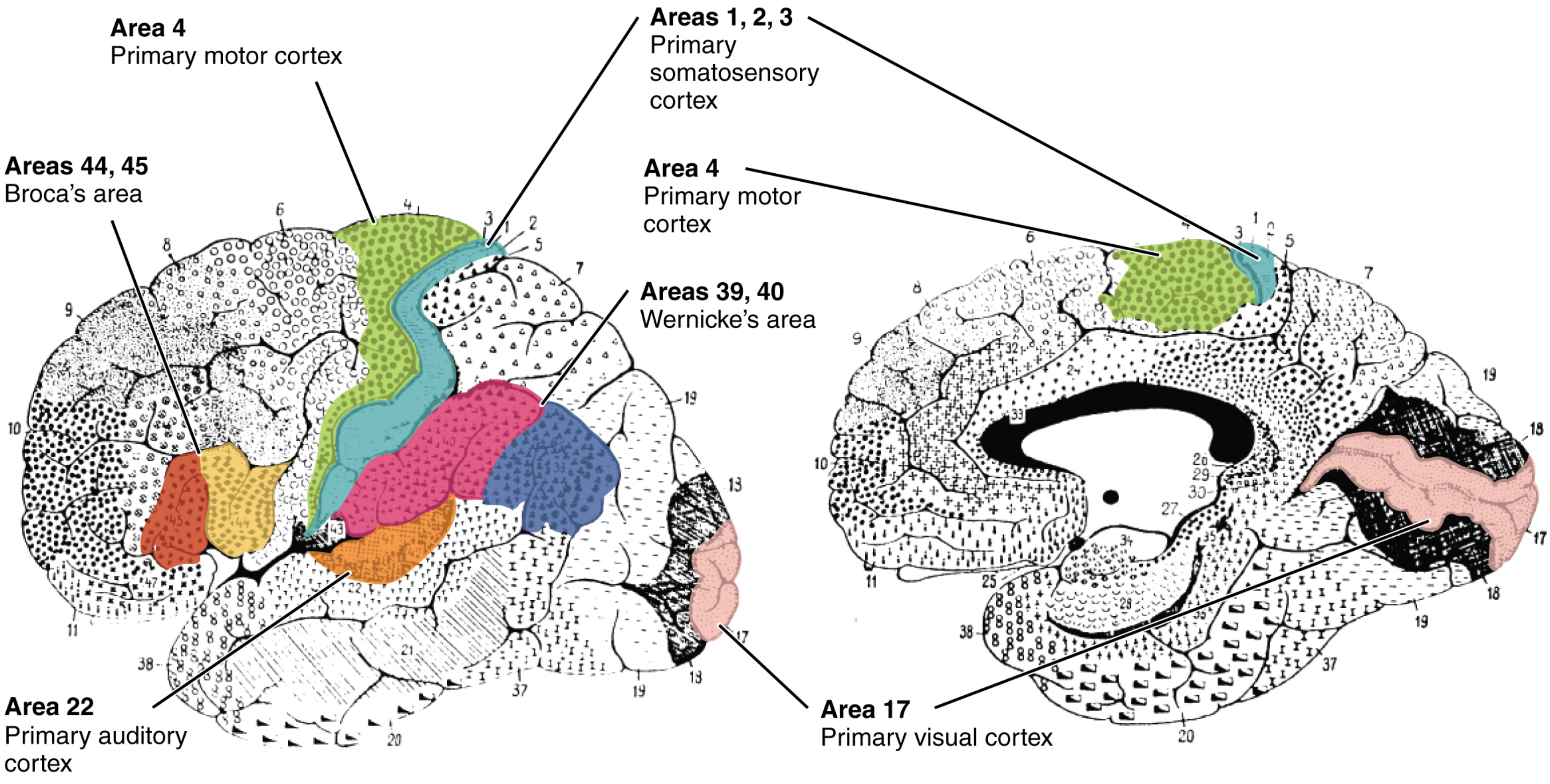
- The fundamental techniques used to analyze resting state BOLD fMRI data
- How a parcellation scheme can be built using these techniques
- Special challenges that result from the hierarchical organization of resting state networks
- How to use supervised learning to build on the data-driven techniques and address these challenges

There are many ways to parcellate the cerebral cortex.

Gyral/sulcal anatomy (AAL)



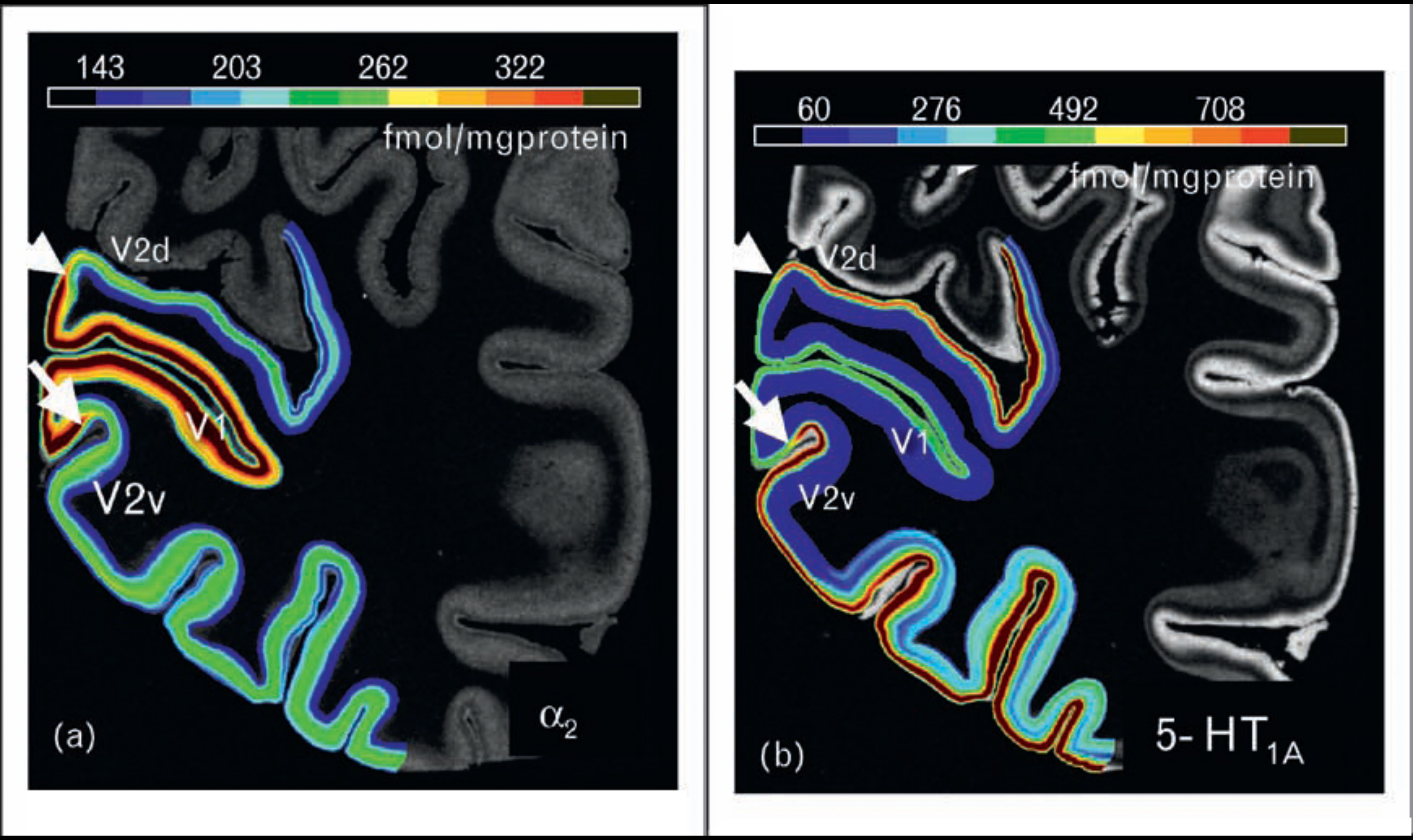
Histology



Brodmann's cytotechtonic map (1909):
Lateral surface

Brodmann's cytotechtonic map (1909):
Medial surface

Receptor density (Zilles & Amunts 2009)

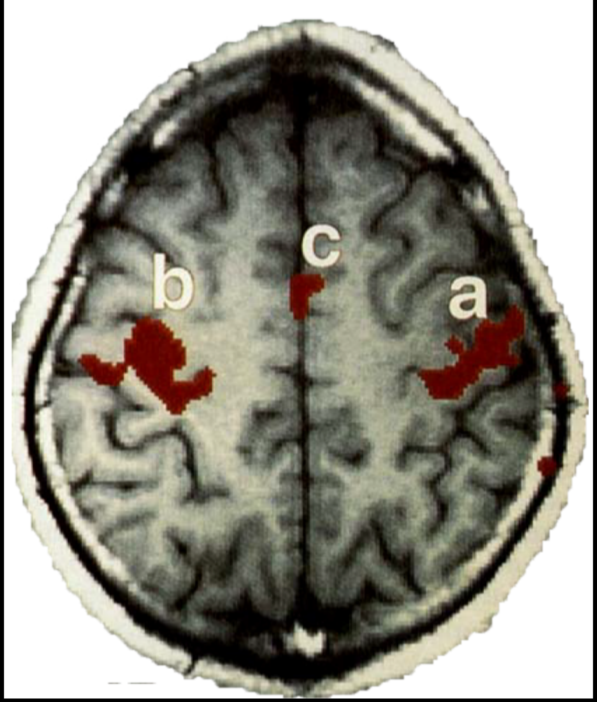


Introduction to resting state functional connectivity (RSFC)

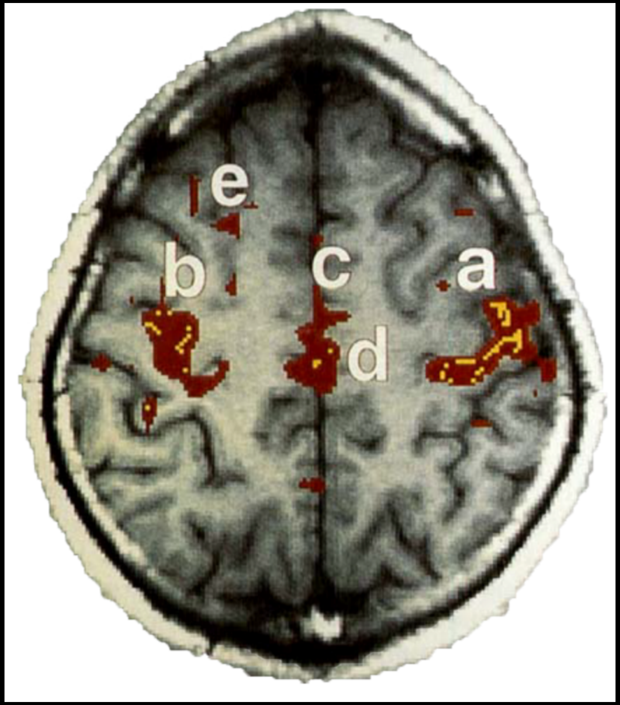
Seed-based Correlation Mapping

- Definition: Spatial map of brain regions correlated with mean time-course of region of interest

Task Response



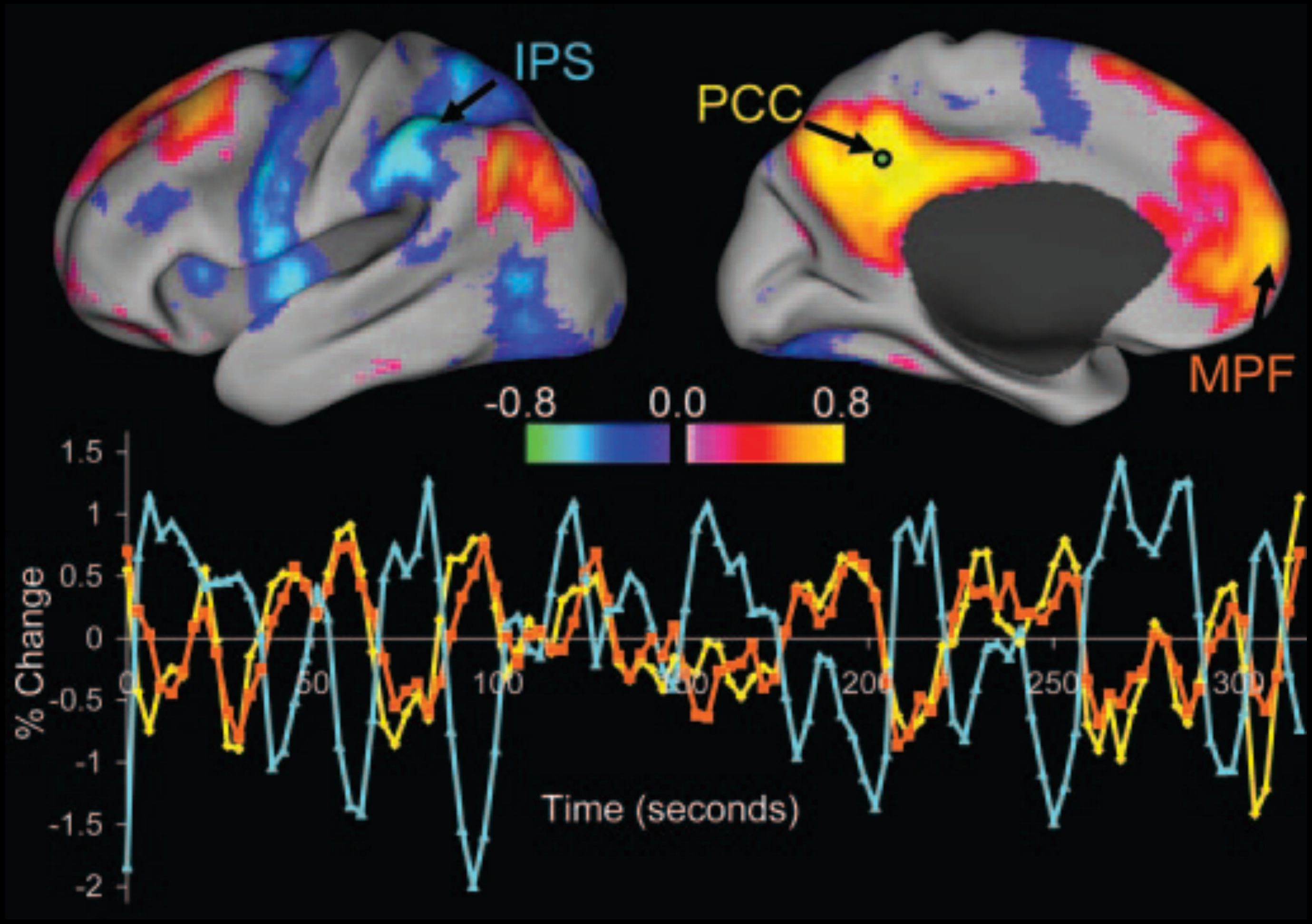
Regions Correlated with "b"



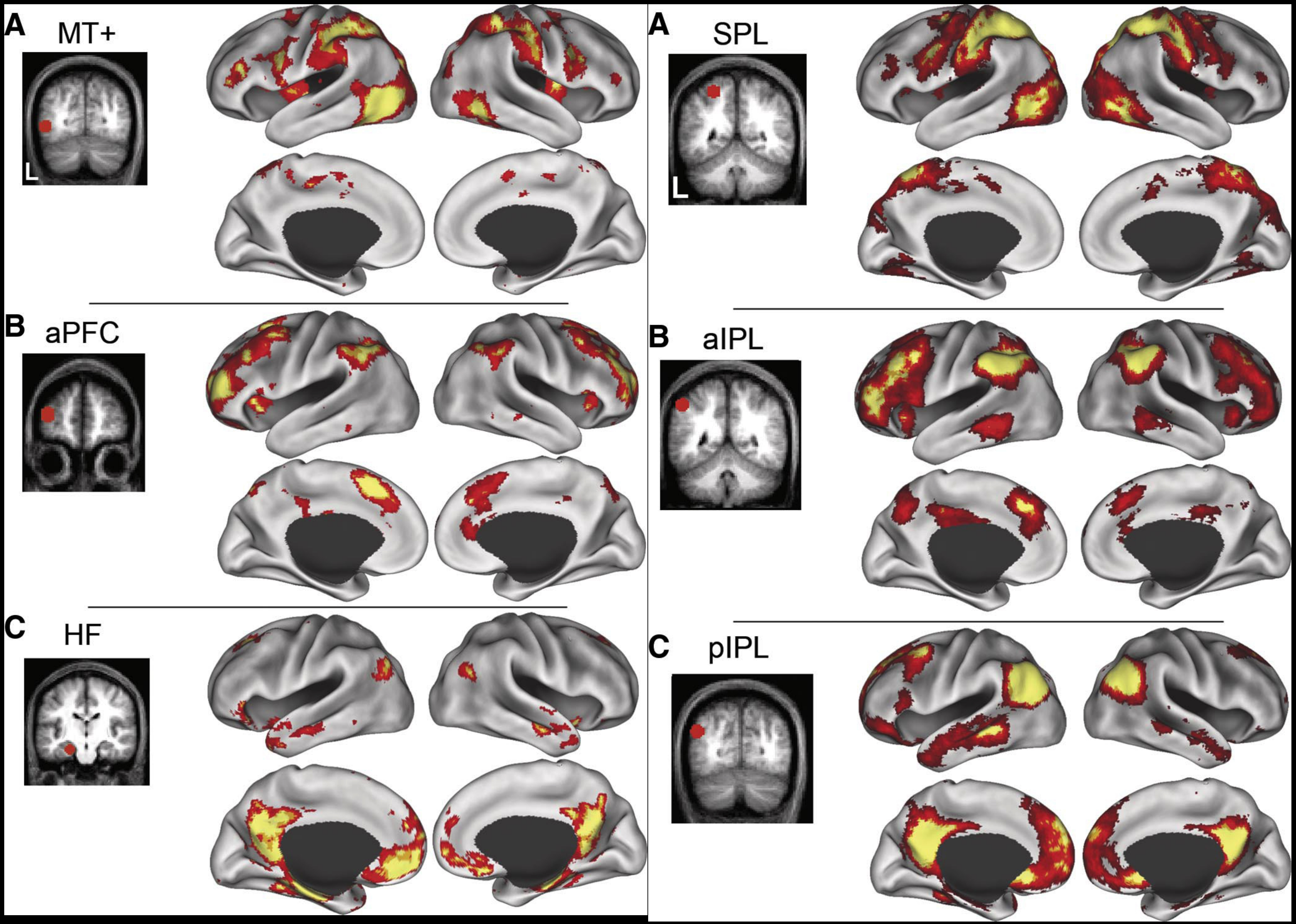
- **Motivation: Regions that correspond to similar brain functions have spontaneously correlated signals**

Biswal et al., 1995

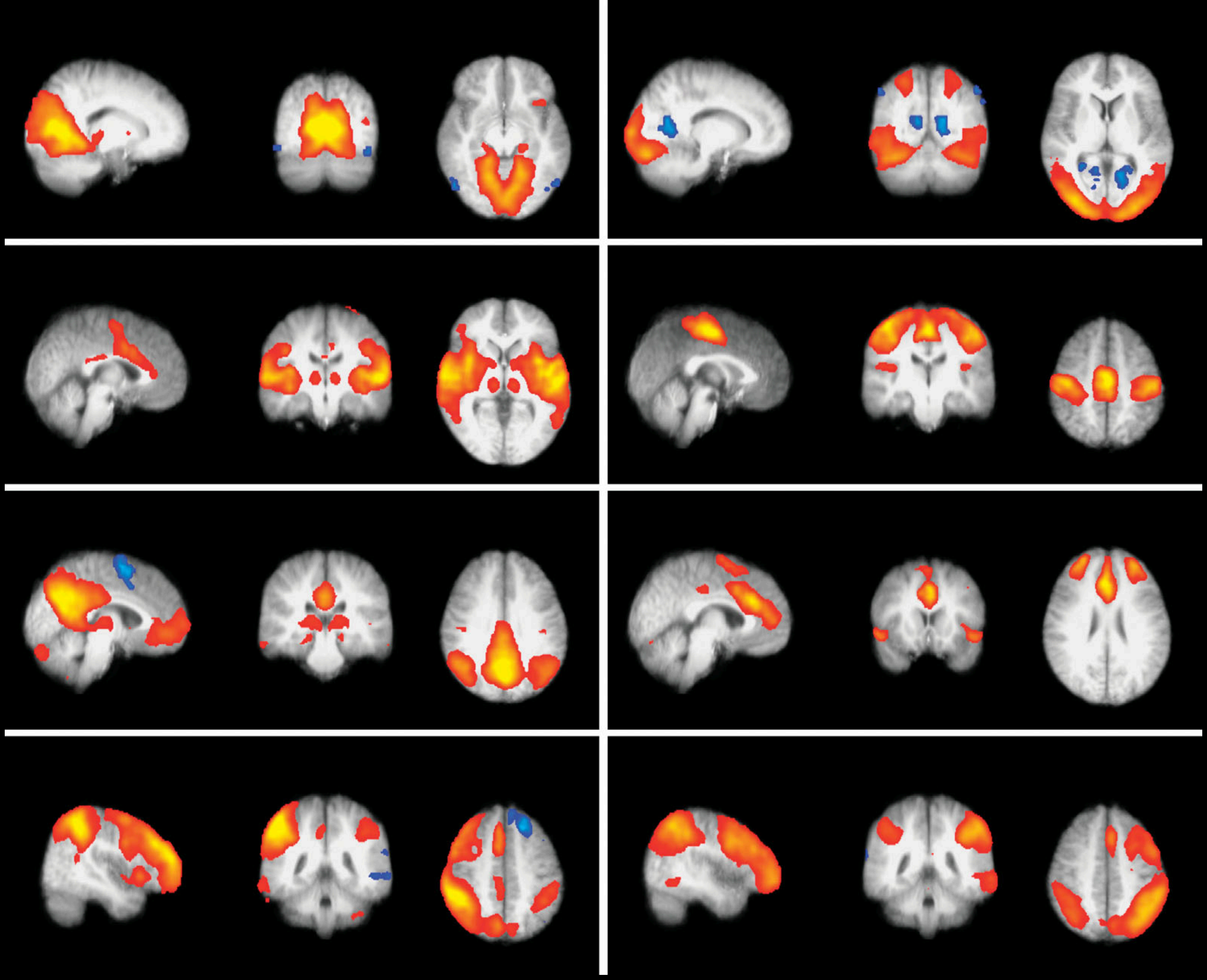
Seed-based Correlation Mapping



Fox et al., PNAS 2005



Vincent et al., J Neurophysiol 2008;100:3328-42



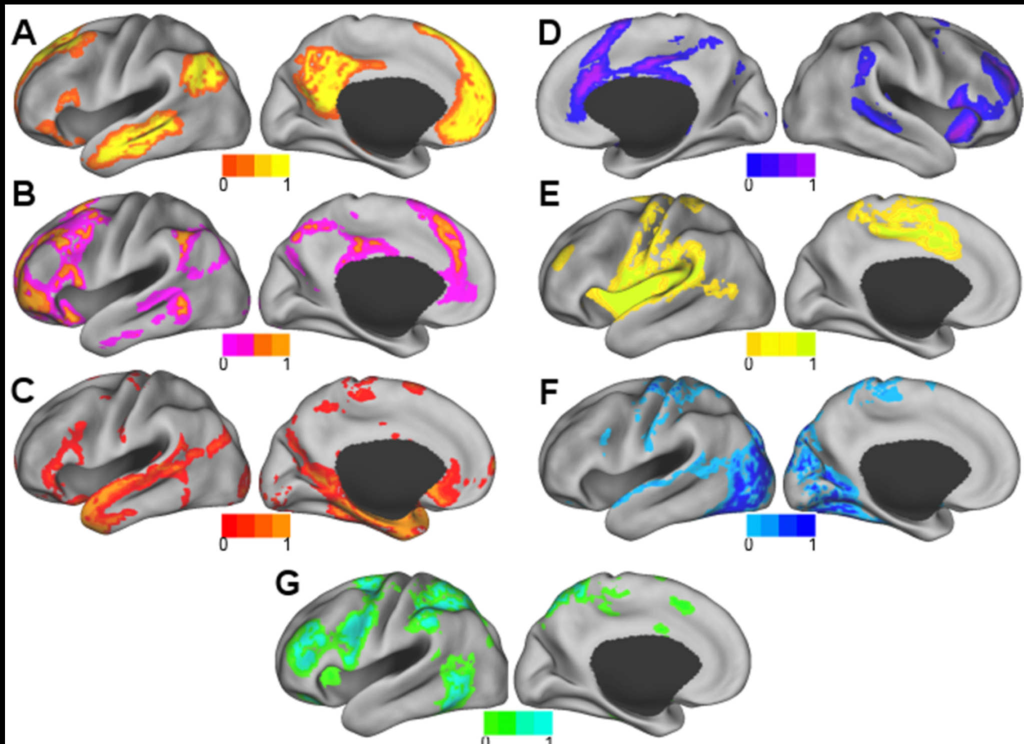
Beckmann et al., TransRSocB 2005

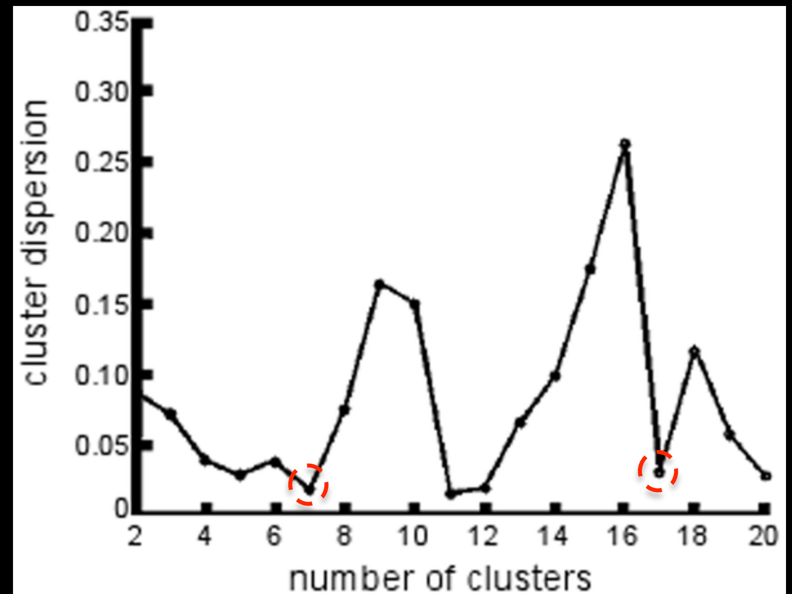
sICA vs. seed-based mapping TECHINICAL COMPARISON

	Spatial ICA (sICA)	Seed-based correlation mapping
Major attribute	Data-driven ("blind")	Directed at pre-determined regions and functional systems
Algorithmic basis	Maximization of component independence	Computation of ROI-voxel correlation (over time)
Noise reduction strategy	Elimination of noise components after sICA	Regression prior to correlation mapping
Combing results over multiple subjects	Concatenation of datasets ("tensor ICA")	Average maps over subjects

Clustering Approaches

- Fuzzy C-means:
  - Each voxel yields one correlation map
  - Clusters are formed from groups of maps with high spatial similarity



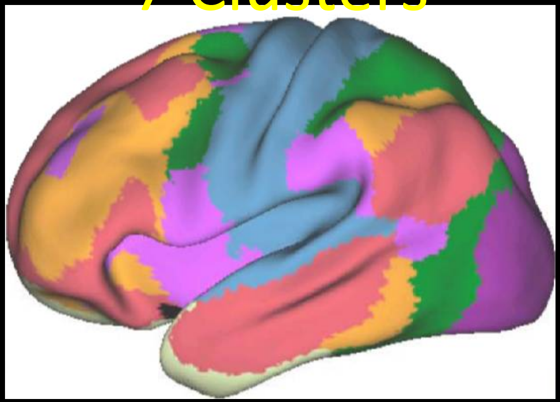


•Multiple "good" answers

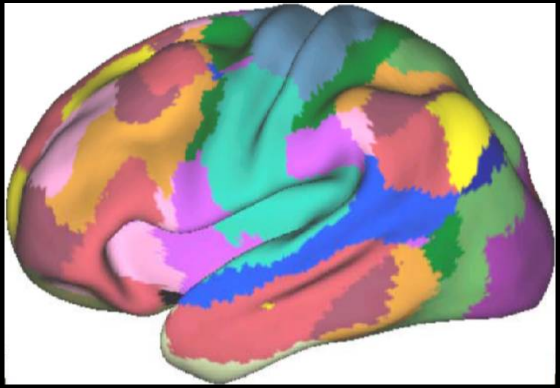
Lee et al., PLoS One (2012)

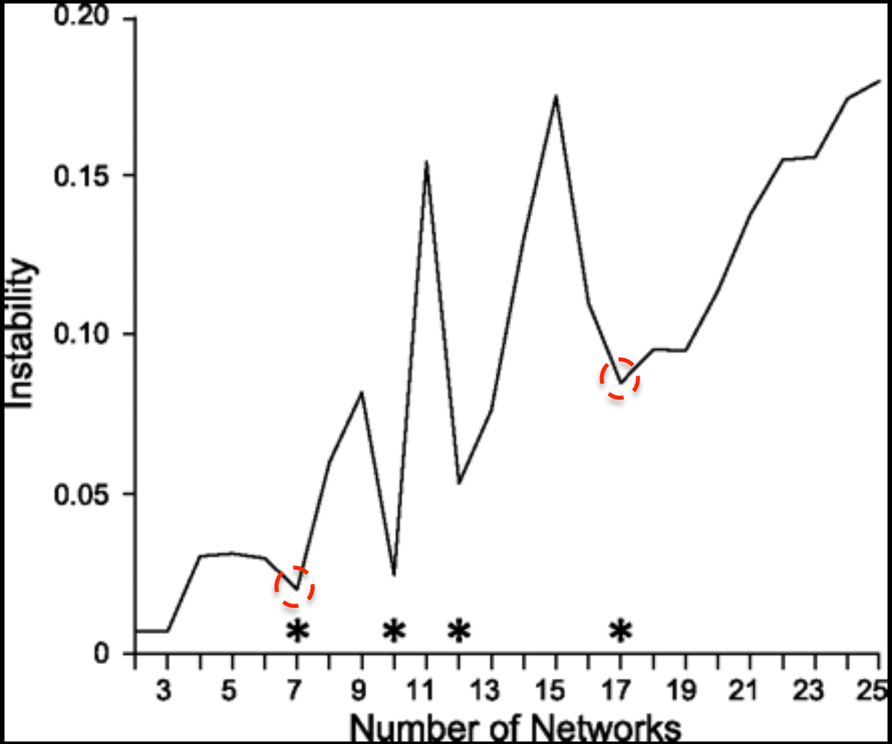
Clustering Approaches

7 Clusters



17 Clusters





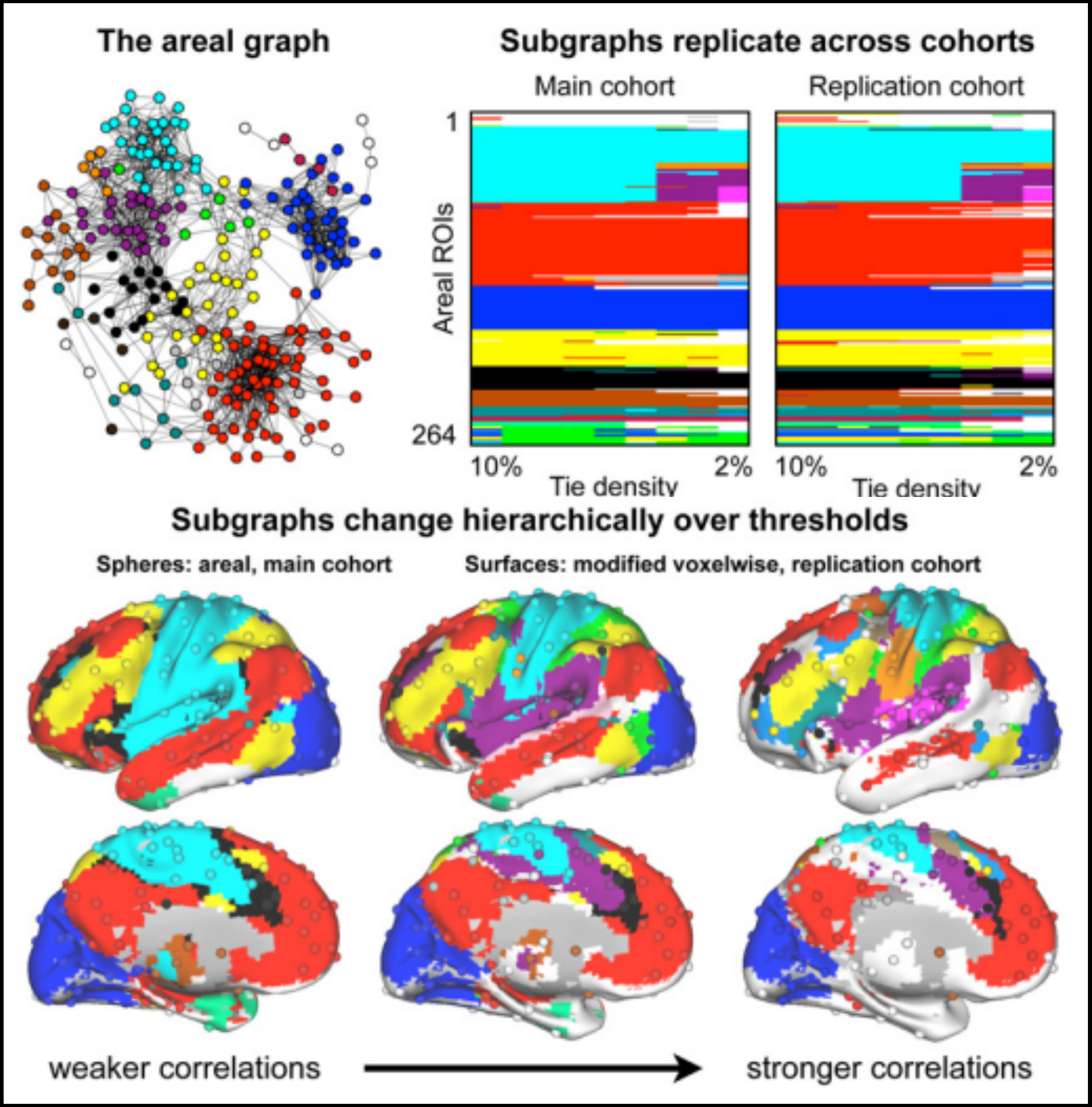
Sub-regions are nested

Multiple local minima in cluster instability

<u>Reproducible, hierarchical organization</u>

Yeo et al., J Neurophysiol (2011)

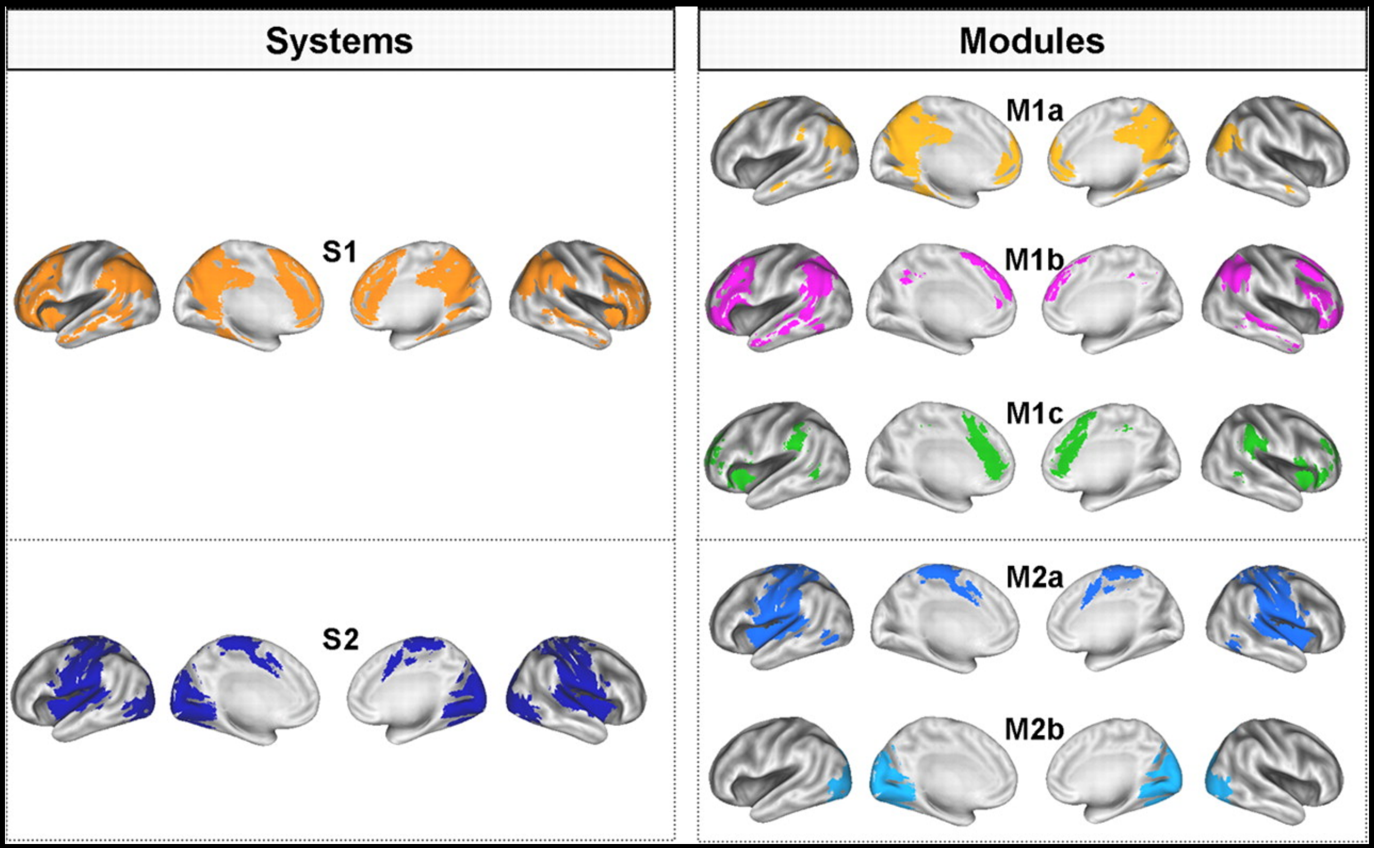
Graph Theoretic Approaches



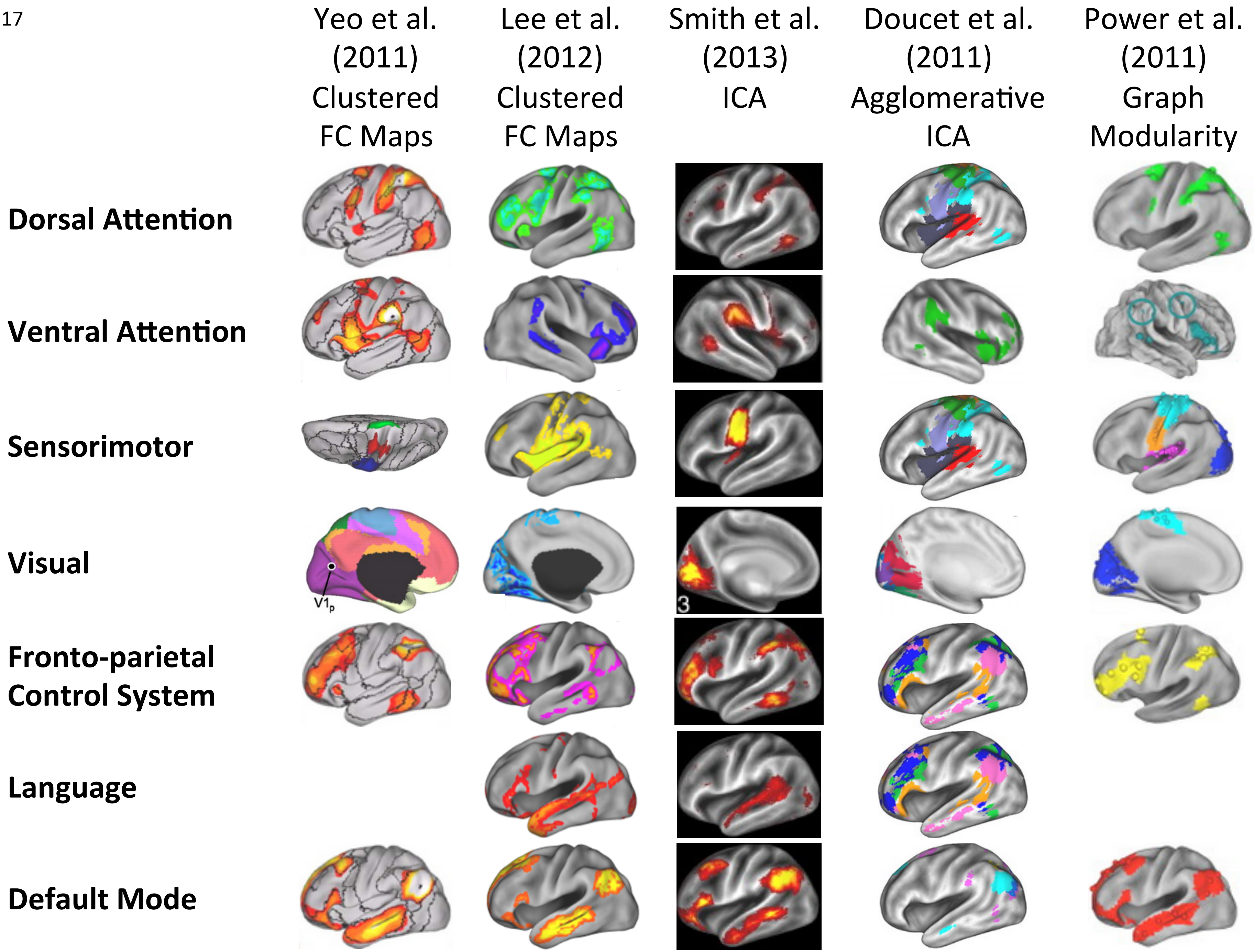
Power et al., Neuron (2011)

RSNs are Hierarchically Organized

- Agglomerative ICA results:
  - RSNs(23) ∈ Modules (5) ∈ Systems(2)



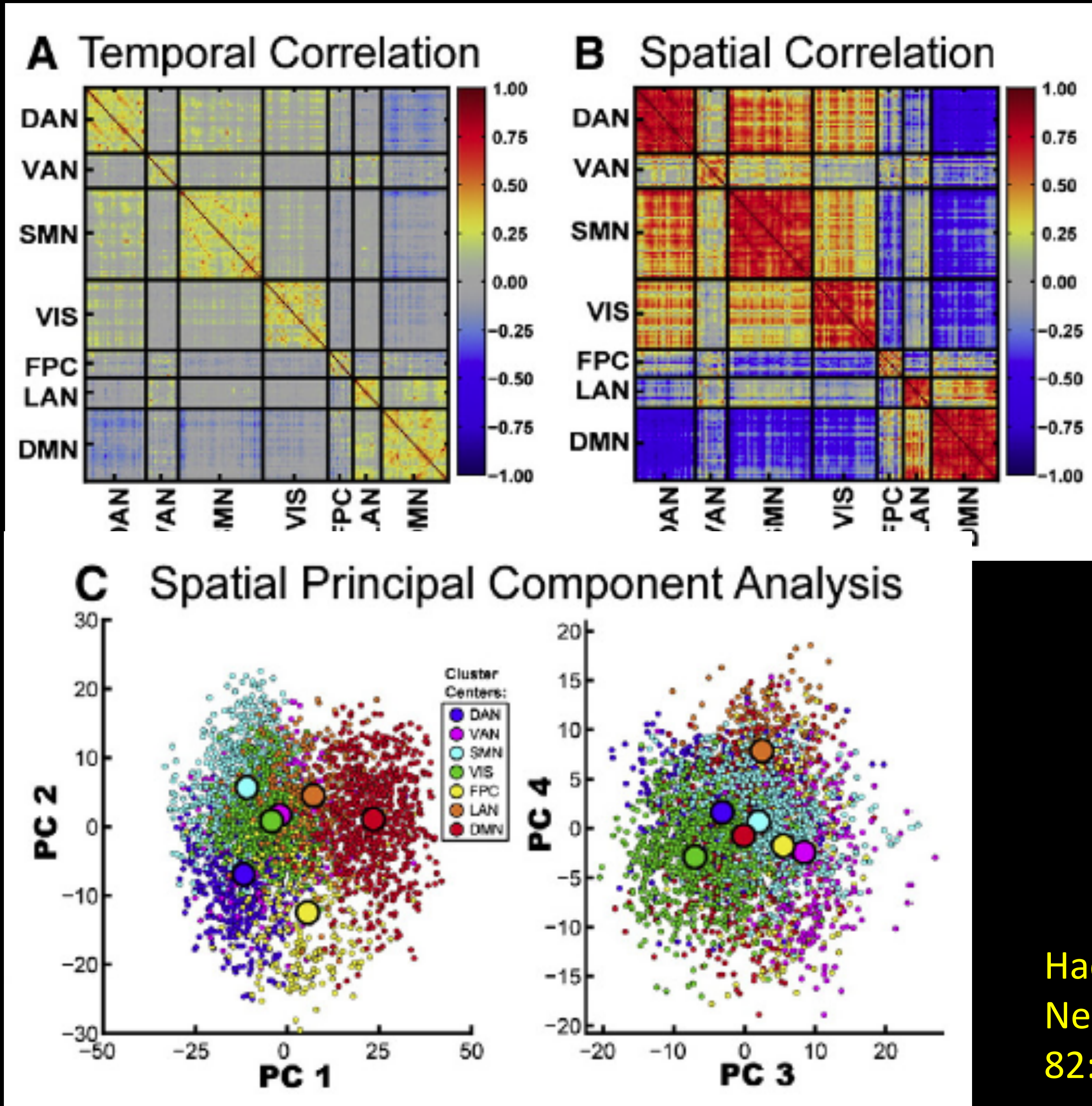
Doucet et al., J Neurophysiol (2011)


Yeo et al. (2011) Clustered FC Maps
Lee et al. (2012) Clustered FC Maps
Smith et al. (2013) ICA
Doucet et al. (2011) Agglomerative ICA
Power et al. (2011) Graph Modularity
Dorsal Attention
Ventral Attention
Sensorimotor
Visual
V1p
3
Fronto-parietal Control System
Language
Default Mode

Parcellation using RSFC gradient mapping

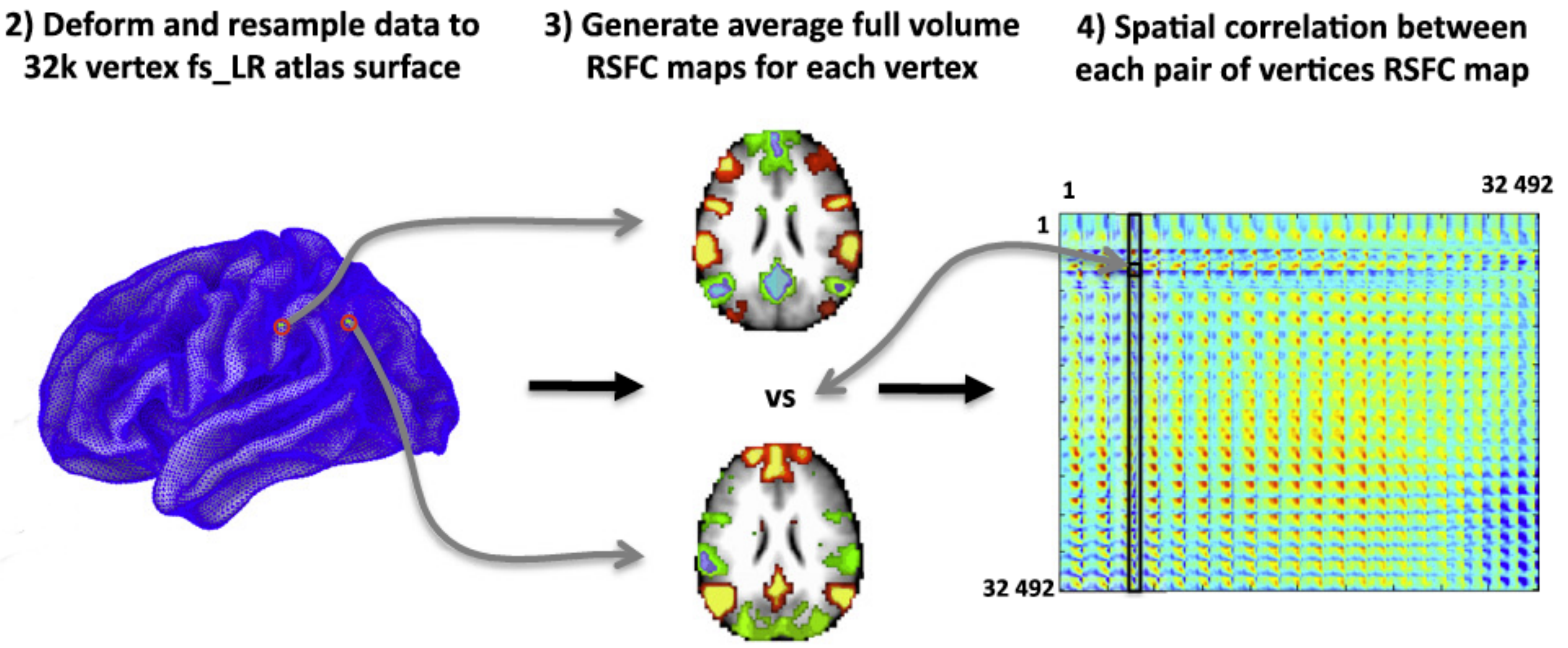

ICELAND
WWW.FREEWORLDMAPS.NET
FAROE ISLANDS
FINLAND
NORWAY
SWEDEN
ESTONIA
RUSSIA
LATVIA
LITHUANIA
IRELAND
UNITED KINGDOM
BELARUS
NETHERLANDS
POLAND
BELGIUM
GERMANY
CZECH REPUBLIC
UKRAINE
LUX.
SLOVAKIA
MOLDOVA
FRANCE
AUSTRIA
SWITZERLAND
HUNGARY
ROMANIA
SLOVENIA
CROATIA
SERBIA
BOSNIA
BULGARIA
PORTUGAL
SPAIN
MON.
KOS.
ITALY
MAC.
ALBANIA
TURKEY
GREECE
CYPRUS

Unlike political maps, resting state network (RSN) maps are not disjoint. Consequently, RSN-based parcellations necessarily involve weighting and thresholding.

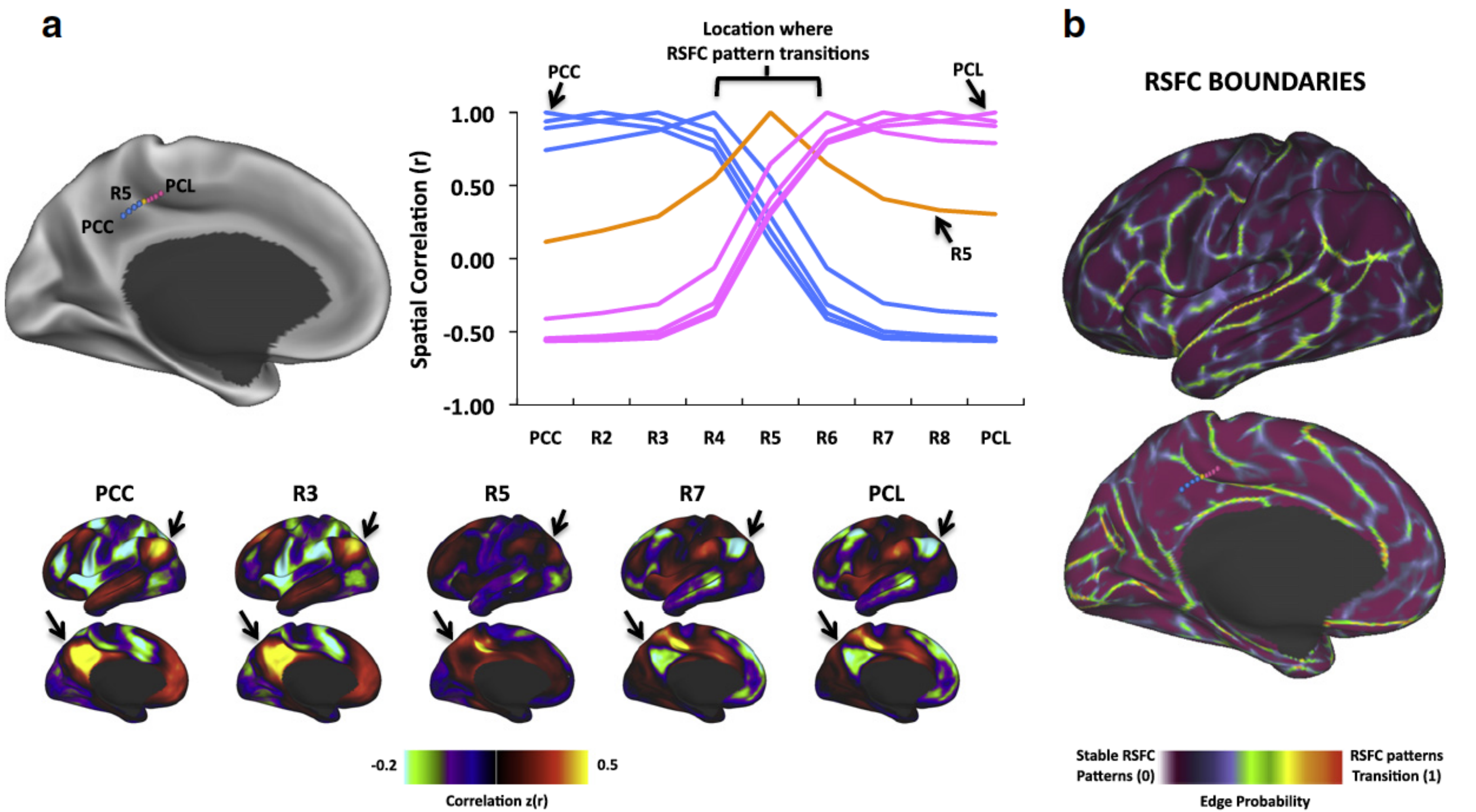


Hacker et al., NeuroImage 2013; 82:616-33

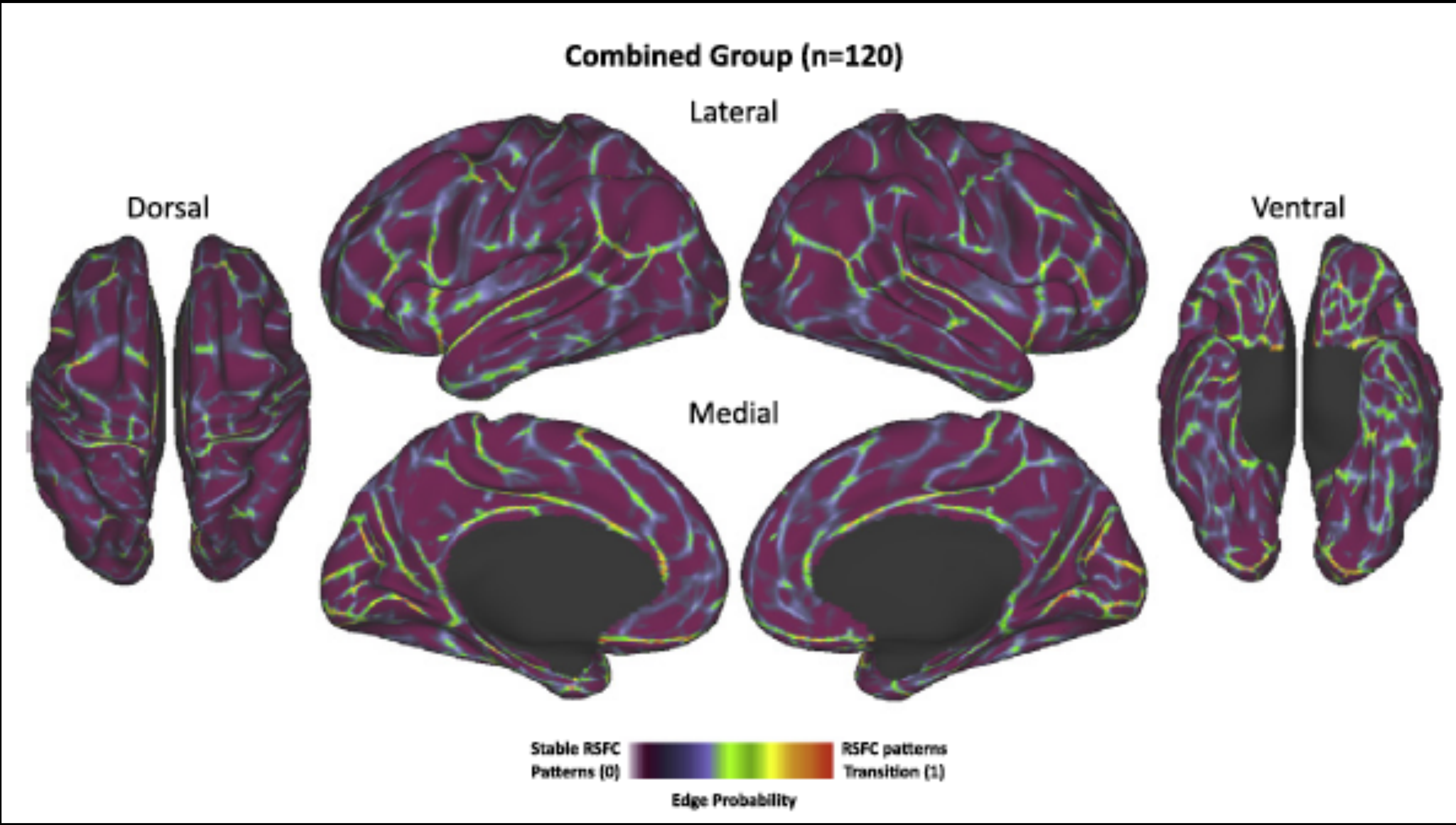
Wig et al., NeuroImage 2014;93:276



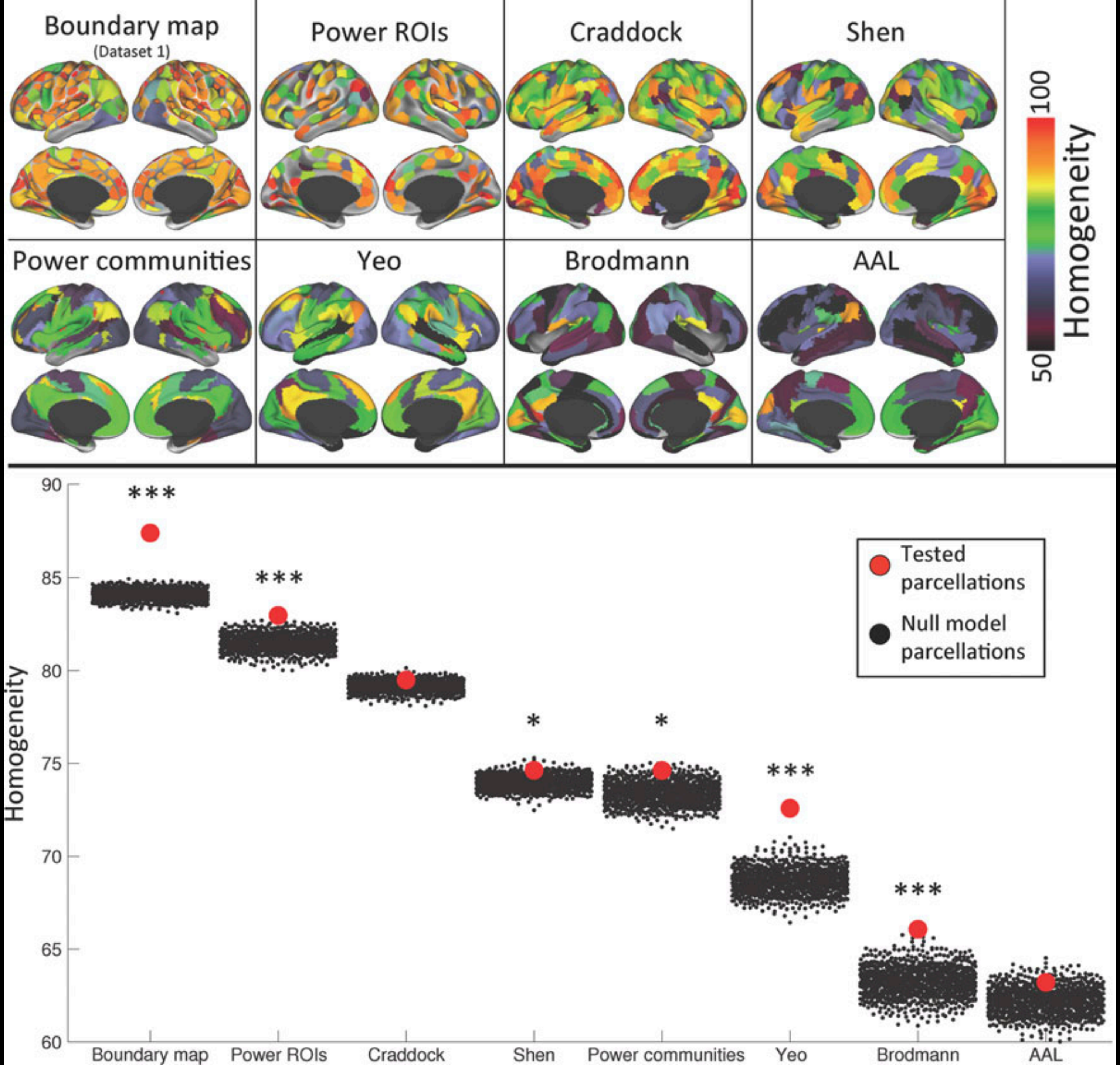
Wig et al., NeuroImage 2014;93:276



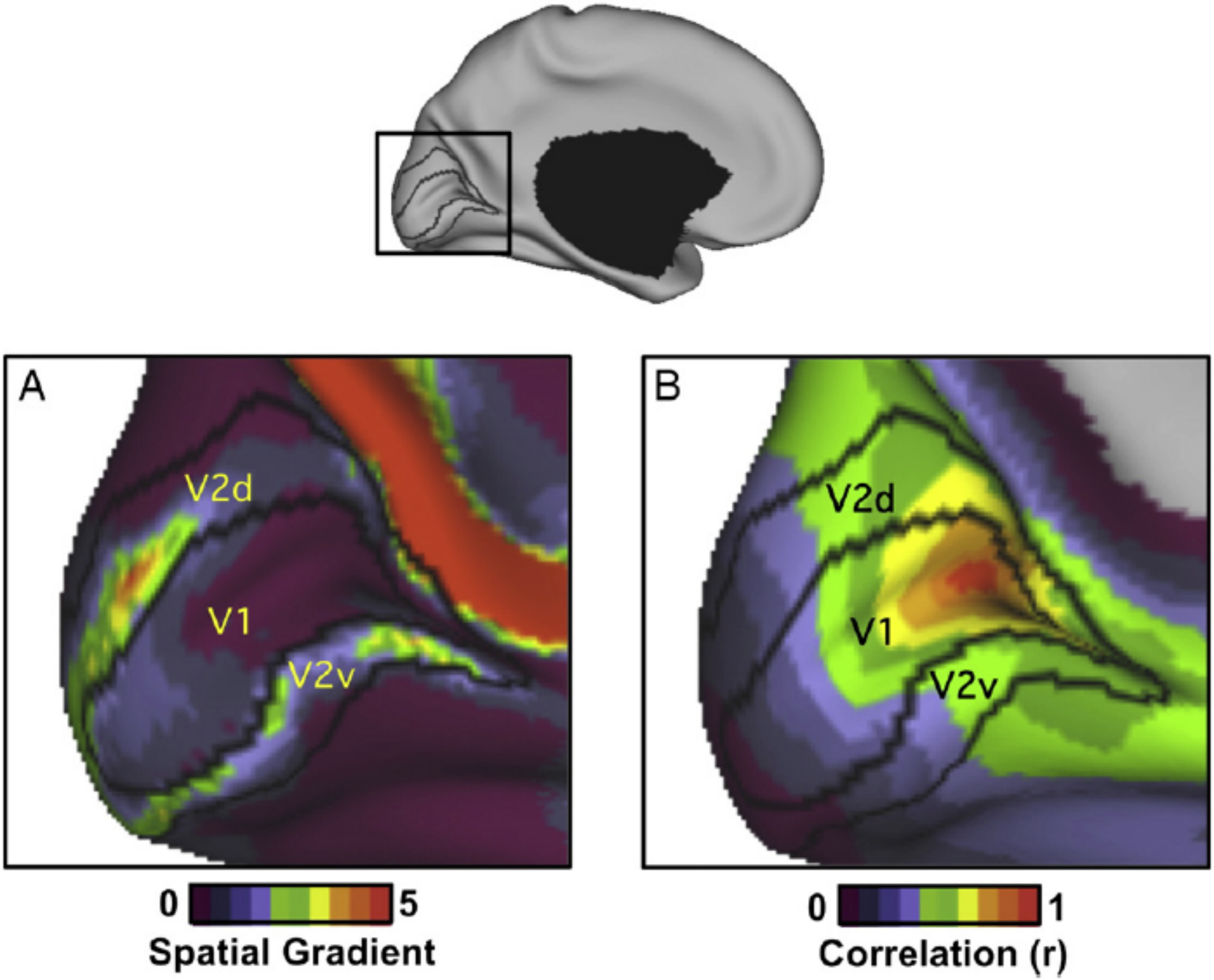
Wig et al., NeuroImage 2014;93:276



RSFC gradients are very unequal in magnitude. The significance of of this essentially topological finding remains unknown.



Boundary map
(Dataset 1)
Power ROIs
Craddock
Shen
Power communities
Yeo
Brodmann
AAL
Homogeneity
100
50
***
***
*
*
***
***
Tested parcellations
Null model parcellations
Homogeneity
90
85
80
75
70
65
60
Boundary map
Power ROIs
Craddock
Shen
Power communities
Yeo
Brodmann
AAL

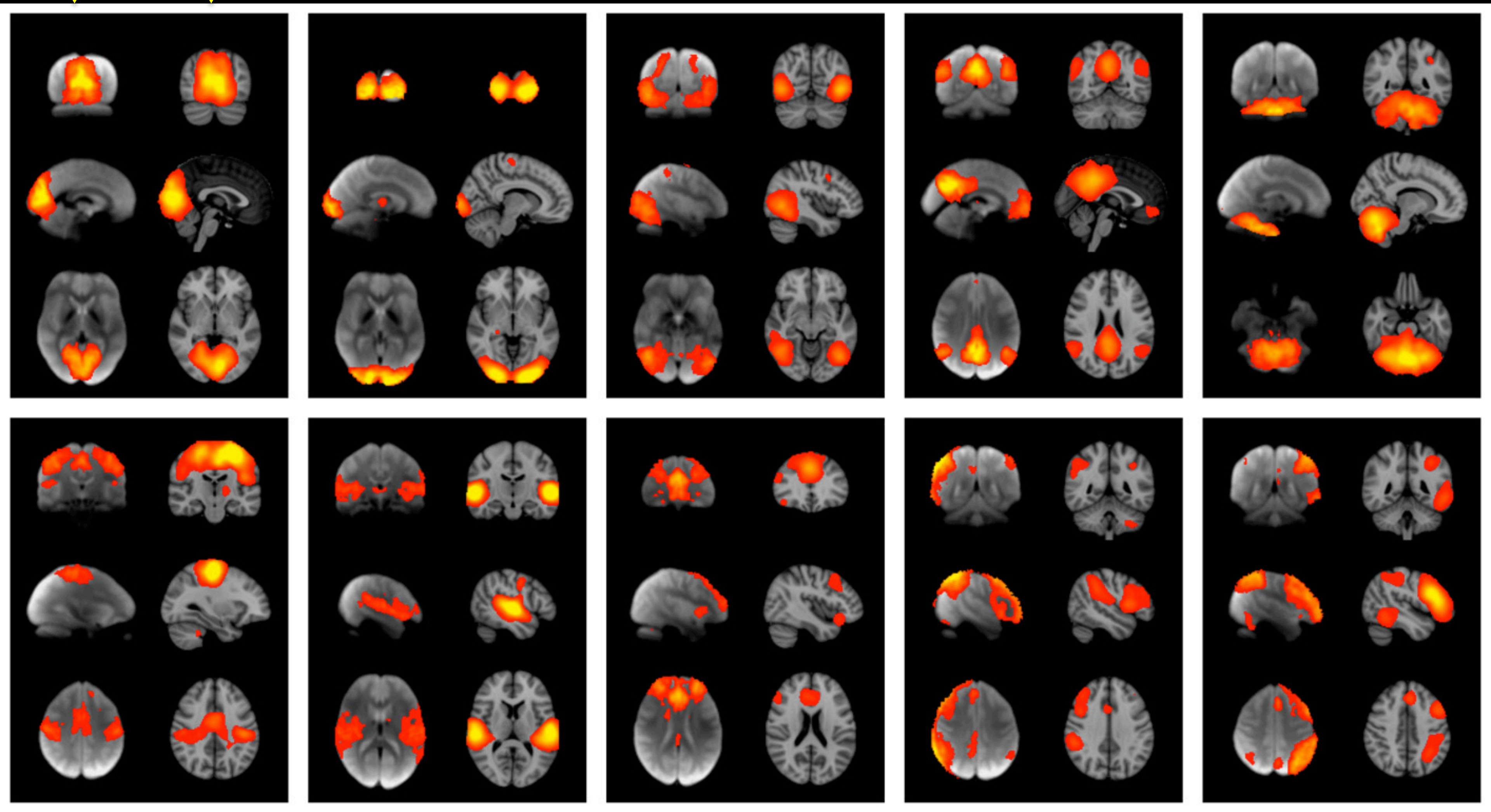

A
V2d
V1
V2v
0
5
Spatial Gradient
B
V2d
V1
V2v
0
1
Correlation (r)

RSFC parcellations in relation to task-fMRI responses

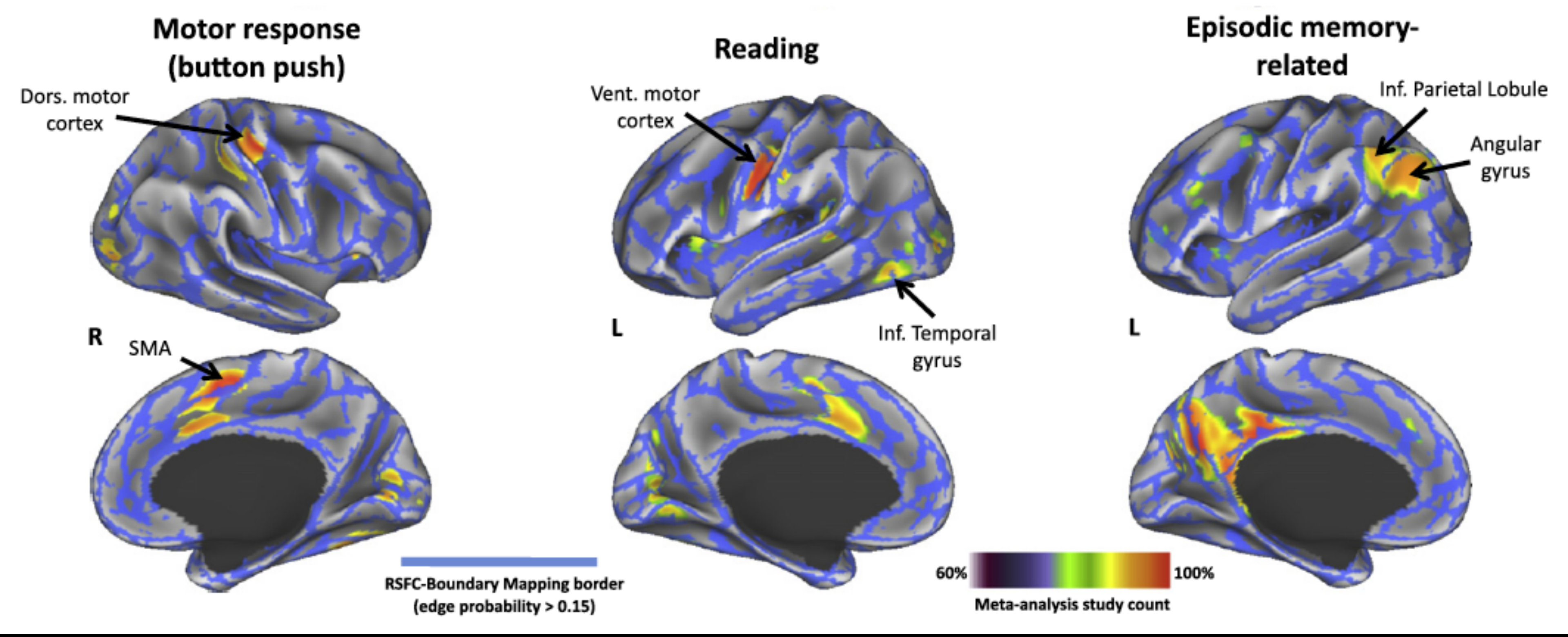
Smith, Fox, et al., PNAS 2009;106:13040-5

RS-fMRI
sICA

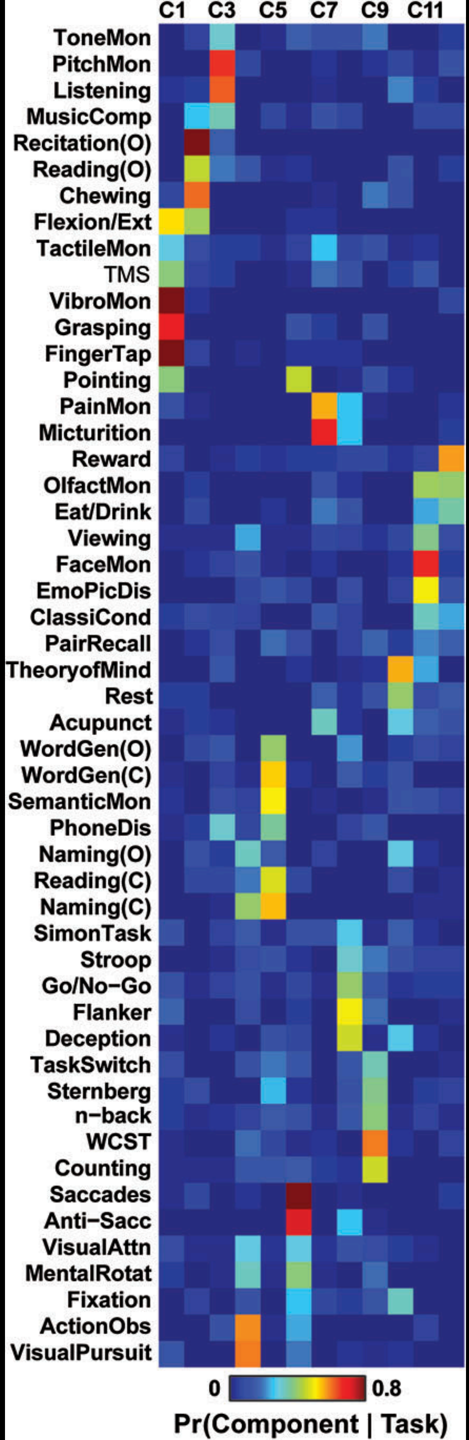
Task-fMRI

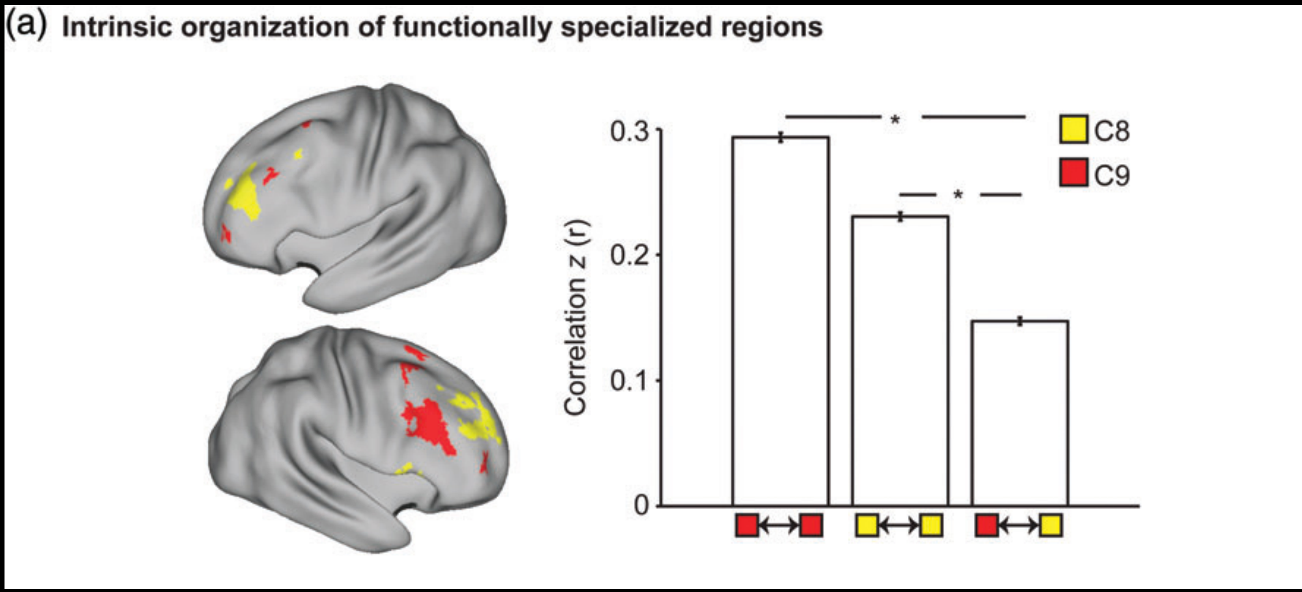


Wig et al., NeuroImage 2014;93:276

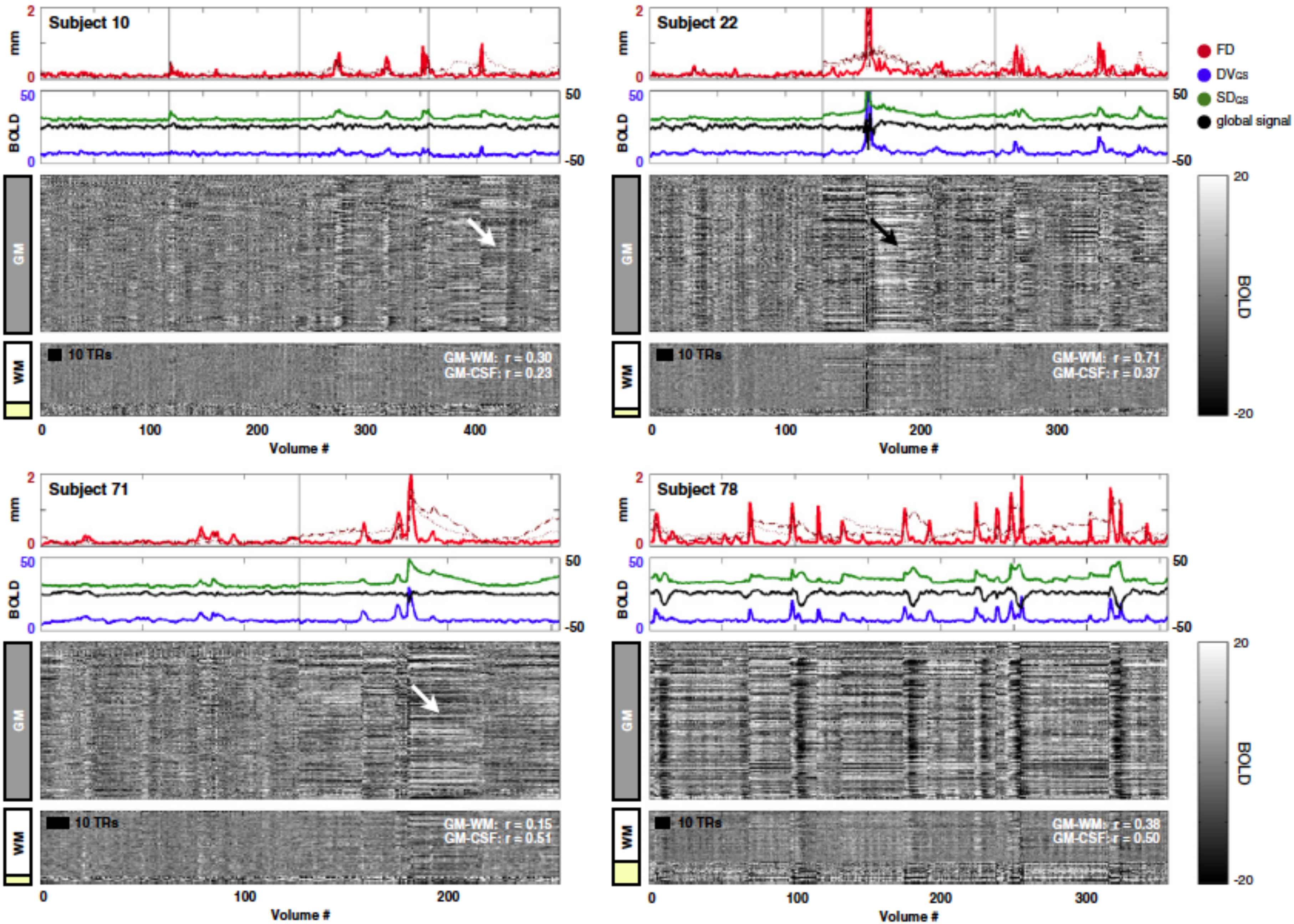


Yeo et al., CerCor 2015;25:3645

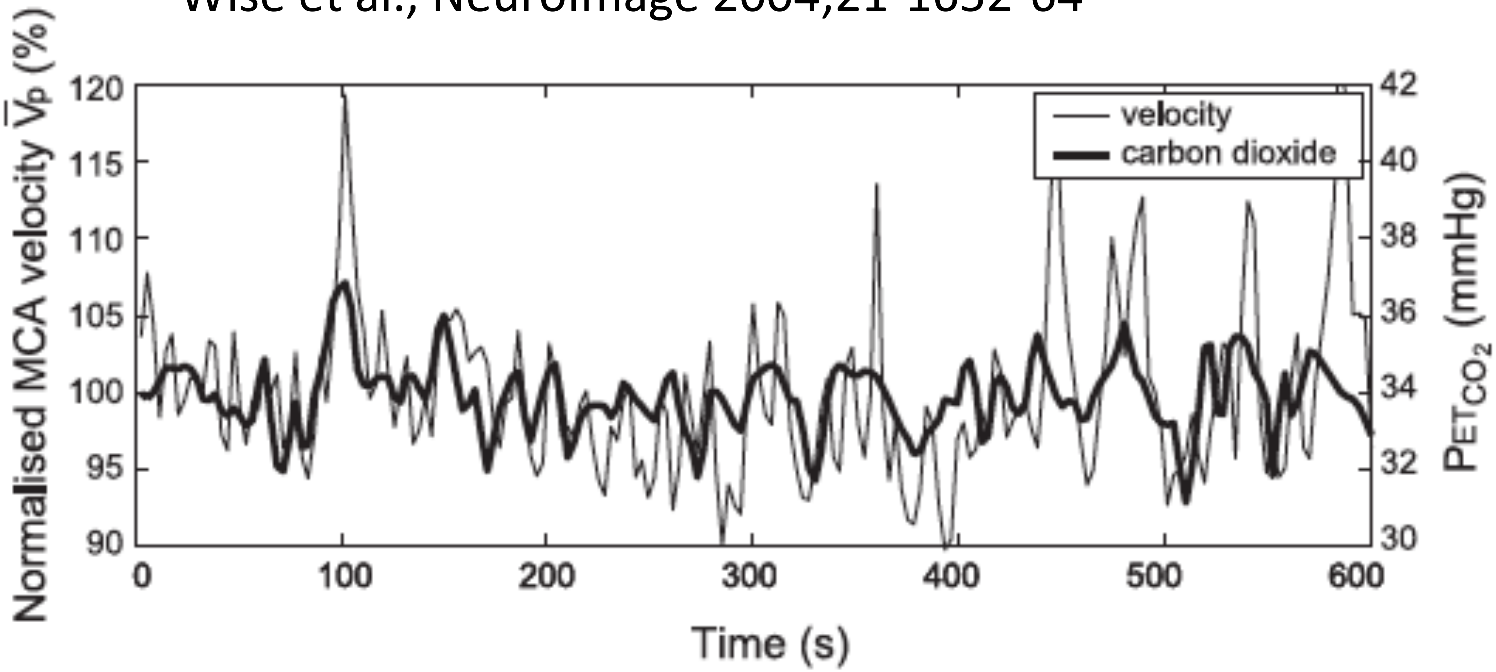


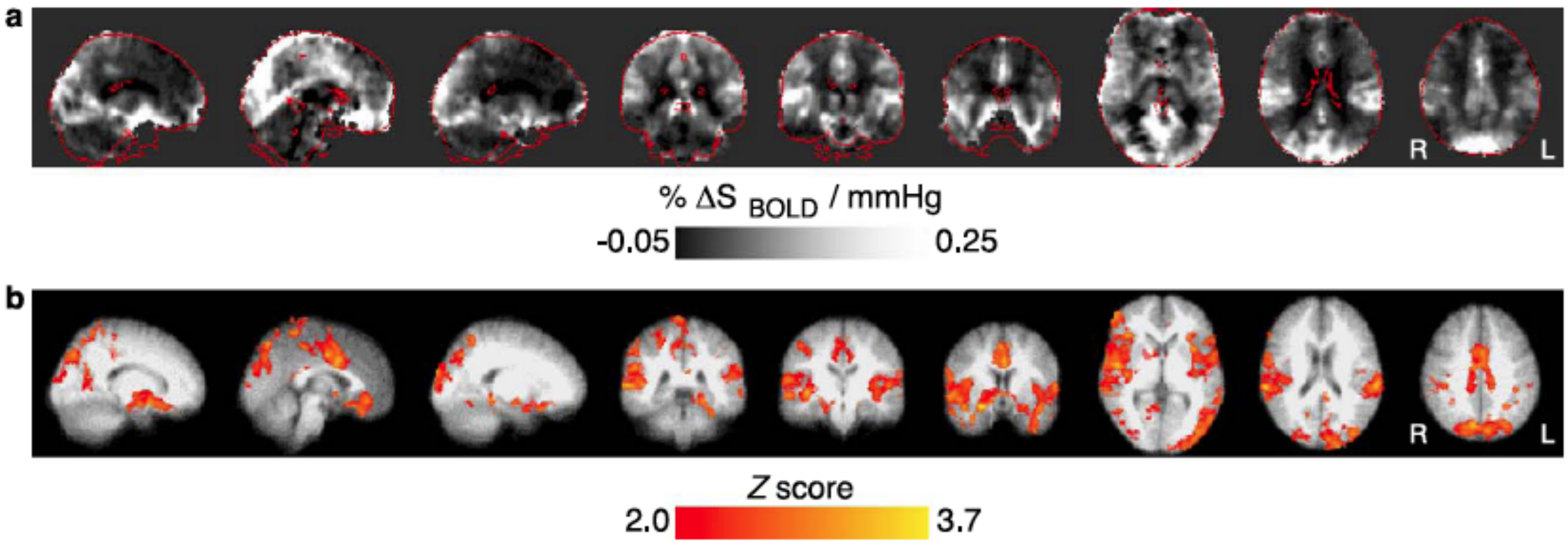


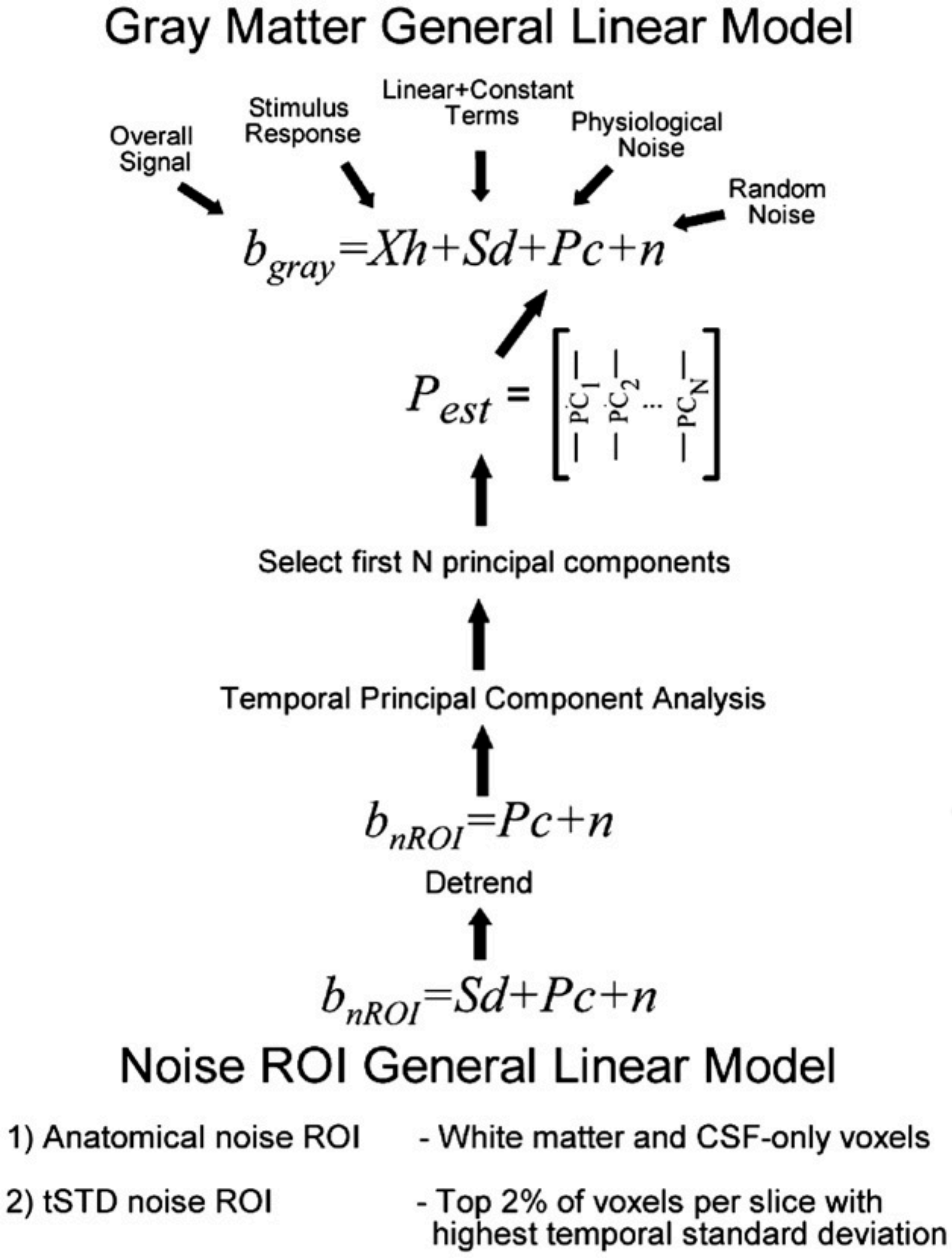
Obtaining good RSFC results requires careful attention to artifact reduction and long acquisitions.


Subject 10
Subject 22
Subject 71
Subject 78
FD
DVcs
SDcs
global signal
mm
BOLD
GM
WM
10 TRs
GM-WM: r = 0.30
GM-CSF: r = 0.23
GM-WM: r = 0.71
GM-CSF: r = 0.37
GM-WM: r = 0.15
GM-CSF: r = 0.51
GM-WM: r = 0.38
GM-CSF: r = 0.50
Volume #

Wise et al., NeuroImage 2004;21-1652-64

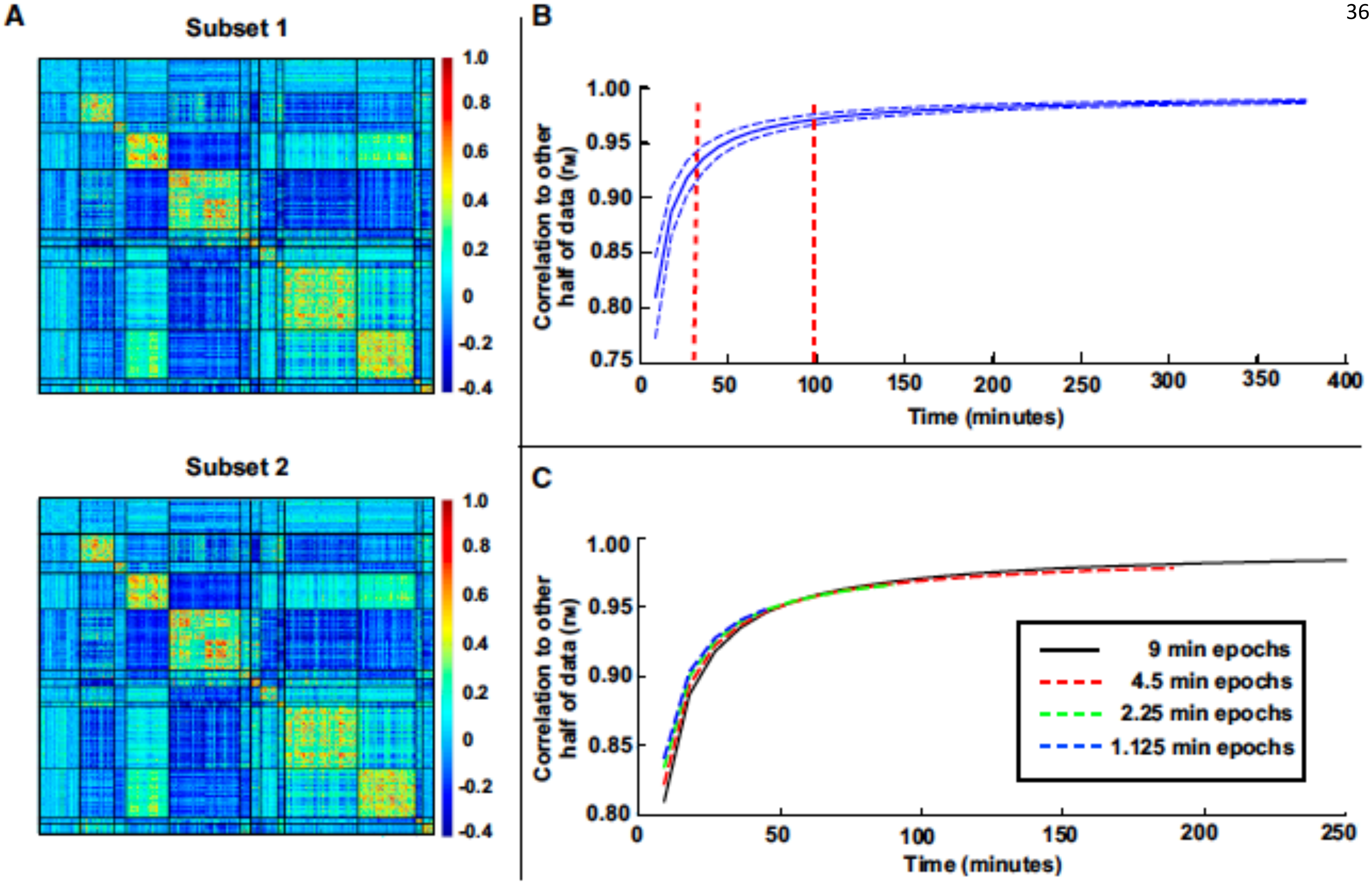






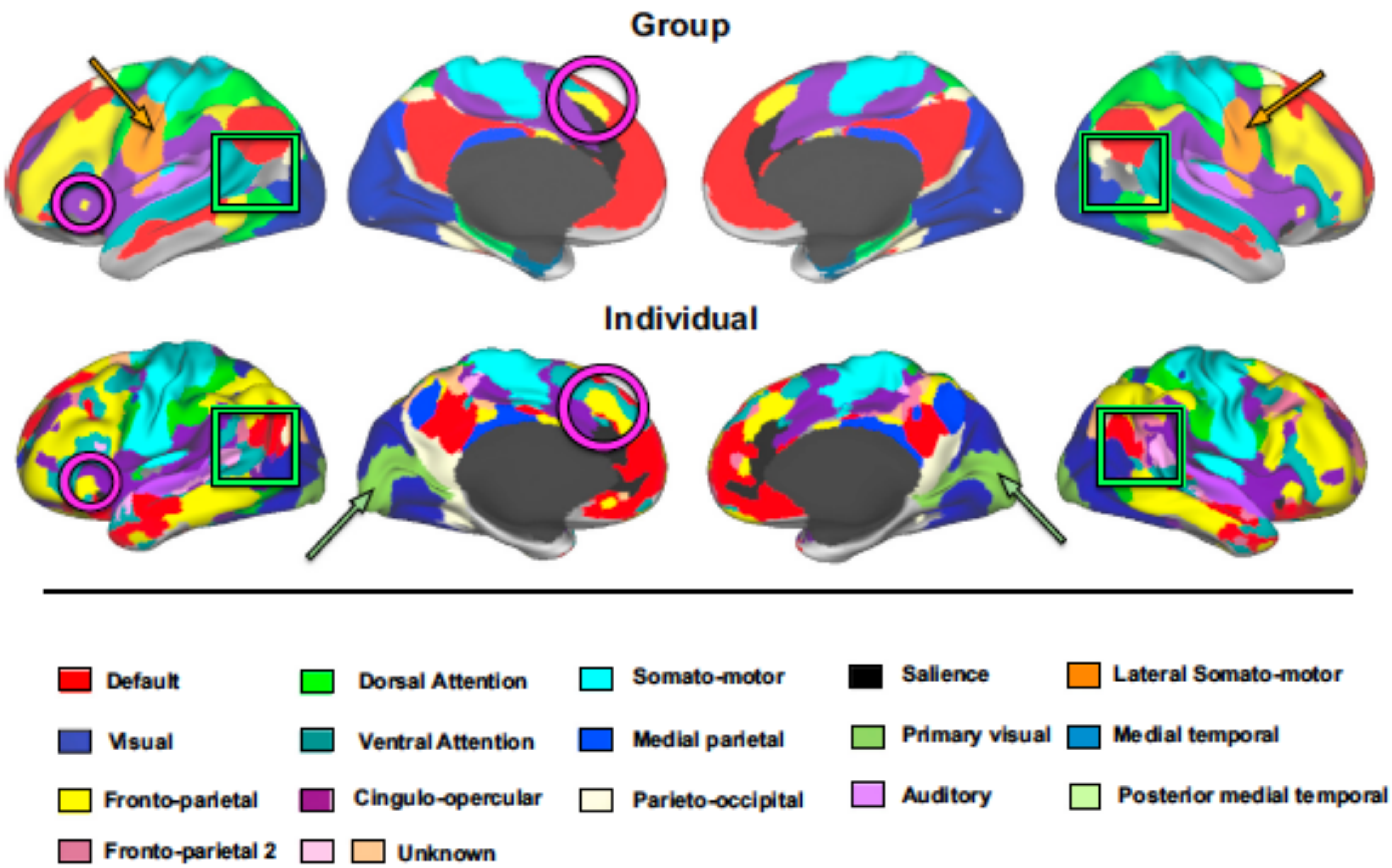
Behzadi et al., NeuroImage 2007; 37:90-101

CompCor scheme



Laumann et al., Neuron 2015;87:1-14

Individual RSN differences



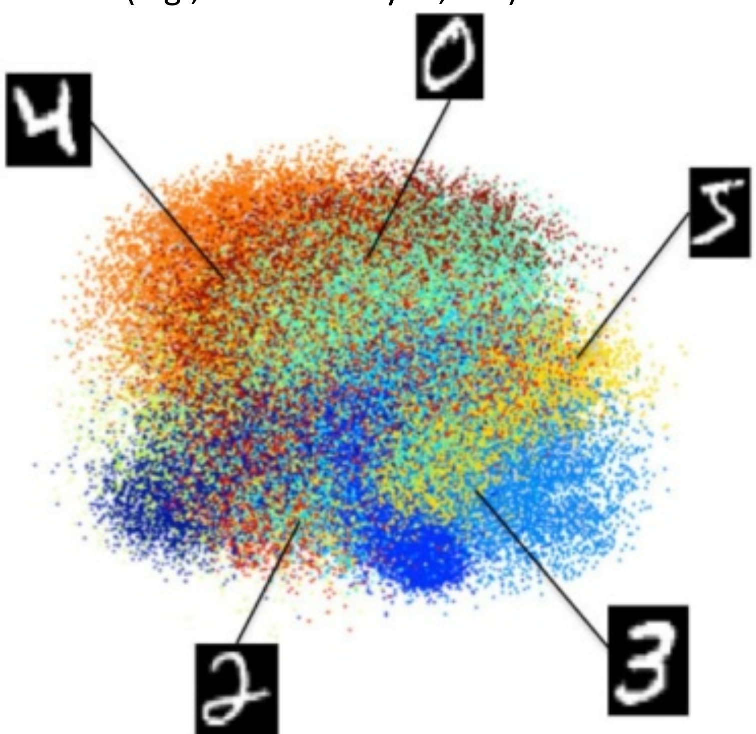
Laumann et al., Neuron 2015;87:1-14

Introduction to supervised classification

Supervised vs. Unsupervised Approaches

Example application:
Automated postal mail sorting

Unsupervised Learning:
(e.g., cluster analysis, ICA)



Bresson et al., 2012

Discovery:
These are the characters of the decimal system

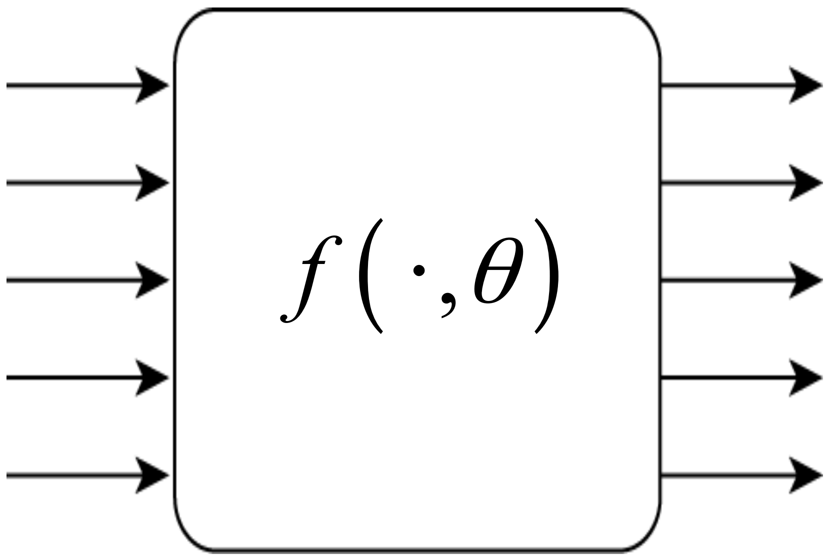
Supervised Learning
• discriminant analysis (LDA/QDA)
• neural networks
• support vector machines

 =“2”

Classification:
This image represents the number “2”

Setting up the problem

Input Space (X):
Array of pixels



Output Space (Y):

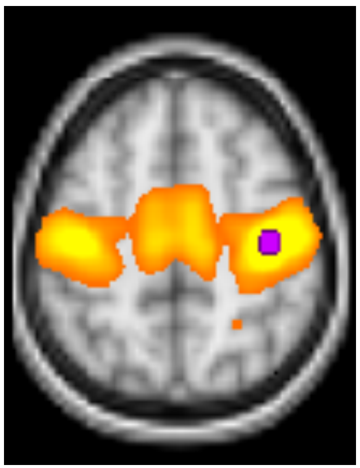
Class	Desired Value
“1”	0
“2”	1
“3”	0
“4”	0
…	0

$$Y \approx f\left(X,\theta\right)$$

Θ - learned model parameters

Setting up the problem

Input Space (X):
Array of voxels



Output Space (Y):

Class	Desired Value
"DAN"	0
"VAN"	0
"SMN"	1
"VIS"	0
…	0

$$f\left(\cdot,\theta\right)$$

$$Y \approx f\left(X,\theta\right)$$

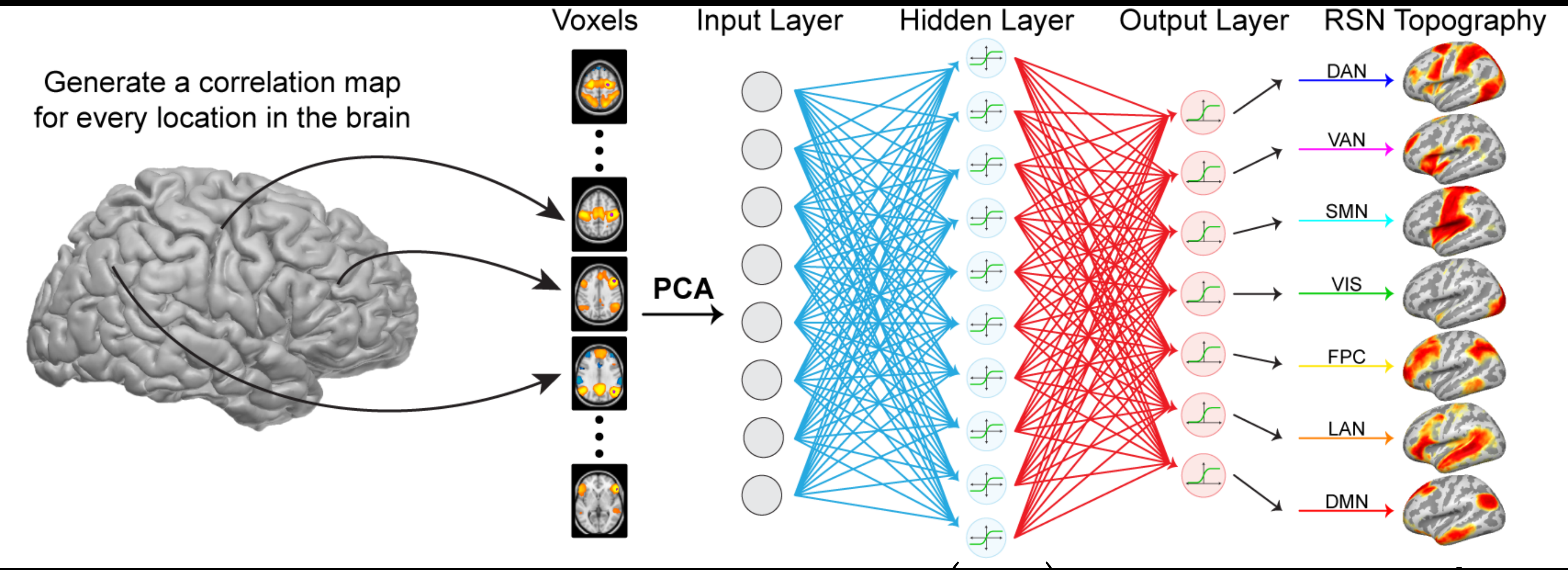
- Training Data:
  – Set of seed-based correlation maps
    - Must include variability across regions and subjects
  – Each seed assigned to one RSN

Supervised Learning

- Theory:
  - Learn an underlying function that maps correlation map topography to RSN identity
- Application:
  - Create correlation map for every region in the brain
  - Apply learned function to these maps
  - Result: map of RSN identity throughout the brain

RSN Classification Technique

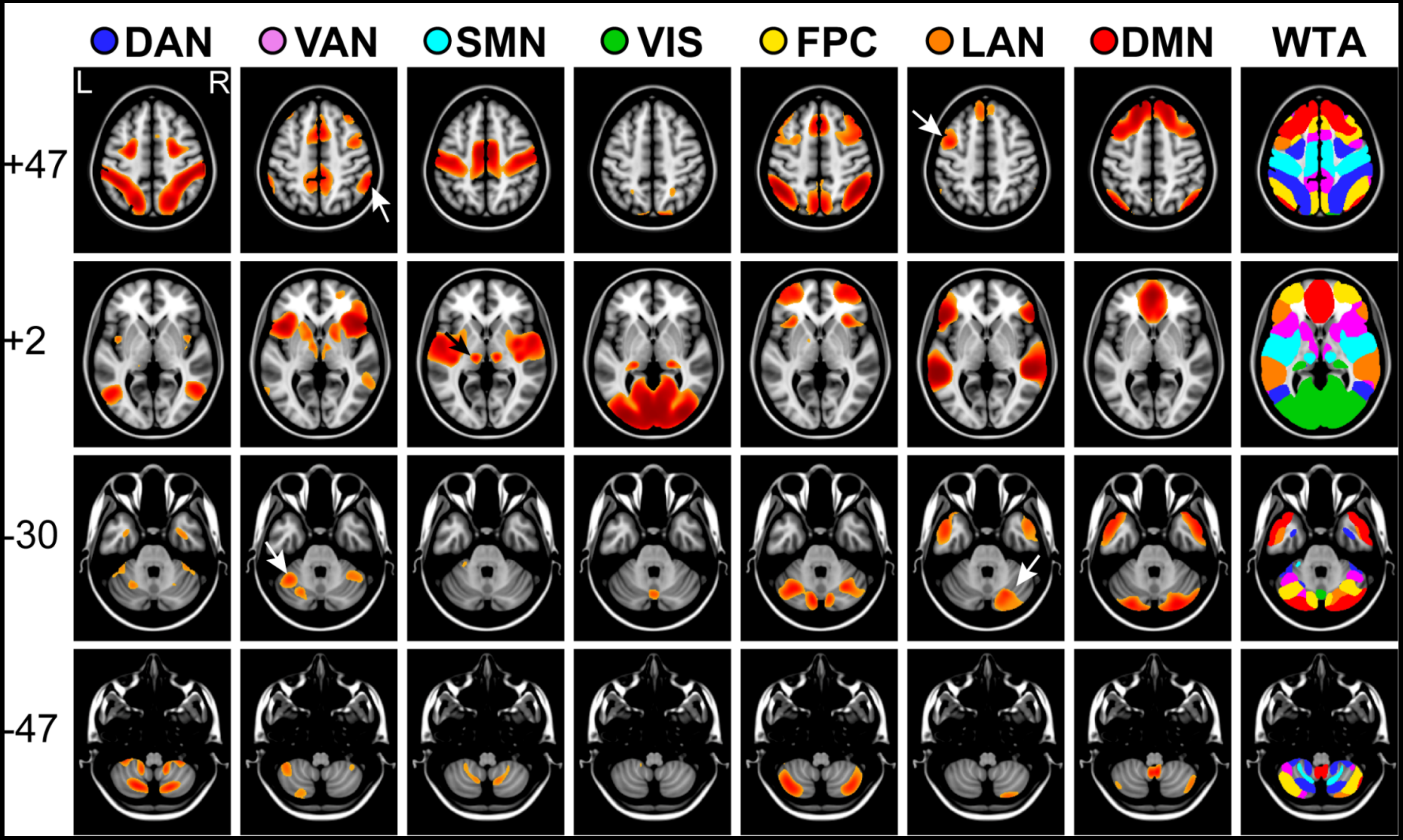
- Compute a correlation map for each point in the brain
- Estimate membership in each RSN class based on learned function



Hacker et al., NeuroImage (2013)

Generalizability to Untrained Brain Regions

- Correct extrapolation to regions not in the training data (cerebellum, thalamus in this example) indicates learning of an underlying function.



Hacker et al., NeuroImage (2013)