



Comparison of Diffusion Kurtosis Imaging to Diffusion Basis Spectrum Imaging in Healthy Young Adults

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INTRODUCTION

Diffusion Tensor Imaging is sensitive to changes in microstructure, but in a way that can be non-specific to the underlying microstructural cause. For example, neurite dispersion and demyelination both lead to decreased FA. These ambiguities in interpretation, as well as advances in image acquisition, have motivated the development of more detailed models of diffusion. Two such models are Diffusion Kurtosis Imaging (DKI) [Jensen 2005] and Diffusion Basis Spectrum Imaging (DBSI) [Ramirez Manzanares 2007]. DKI is a mathematical model of the higher-order properties of the diffusion profile, while DBSI is a biophysically informed model of the underlying tissue microstructure.

Three commonly used measures from DKI are: Mean Kurtosis (MK) Axial Kurtosis (AK), Radial Kurtosis(RK). These parameters represent the degree of nongaussianity in the diffusion profile generally for MK, parallel to the principal diffusion direction for AK, and perpendicular for RK. For DBSI, there are four main measures: Water Ratio (WR), Fiber Ratio (FR), Hindered Ratio (HR) and Restricted Ratio (RR). These measures represent the proportion of signal assigned to various compartments by the DBSI model, and they sum to unity.

These models have not been directly compared in humans. In this study, we examined the relationship between the parameters calculated using both of these models fitted to the same diffusion data in healthy young adults. This is an exploratory study of the relationship between DKI and DBSI parameters across multiple human subjects.

RESULTS

Figure 1 shows the regions where HR, WR and RR dominate, averaged across individuals. FR was not consistently dominant across any regions. Figure 2 shows scatterplots of DKI and DBSI parameters across all subjects. When considering these relationships separately across subjects, the maximum intersubject standard deviation among all 12 r_s values (3 DKI measures x 4 DBSI measures) was 0.058, which was for the HR-AK correlation. This indicates that these relationships are stable across individuals.

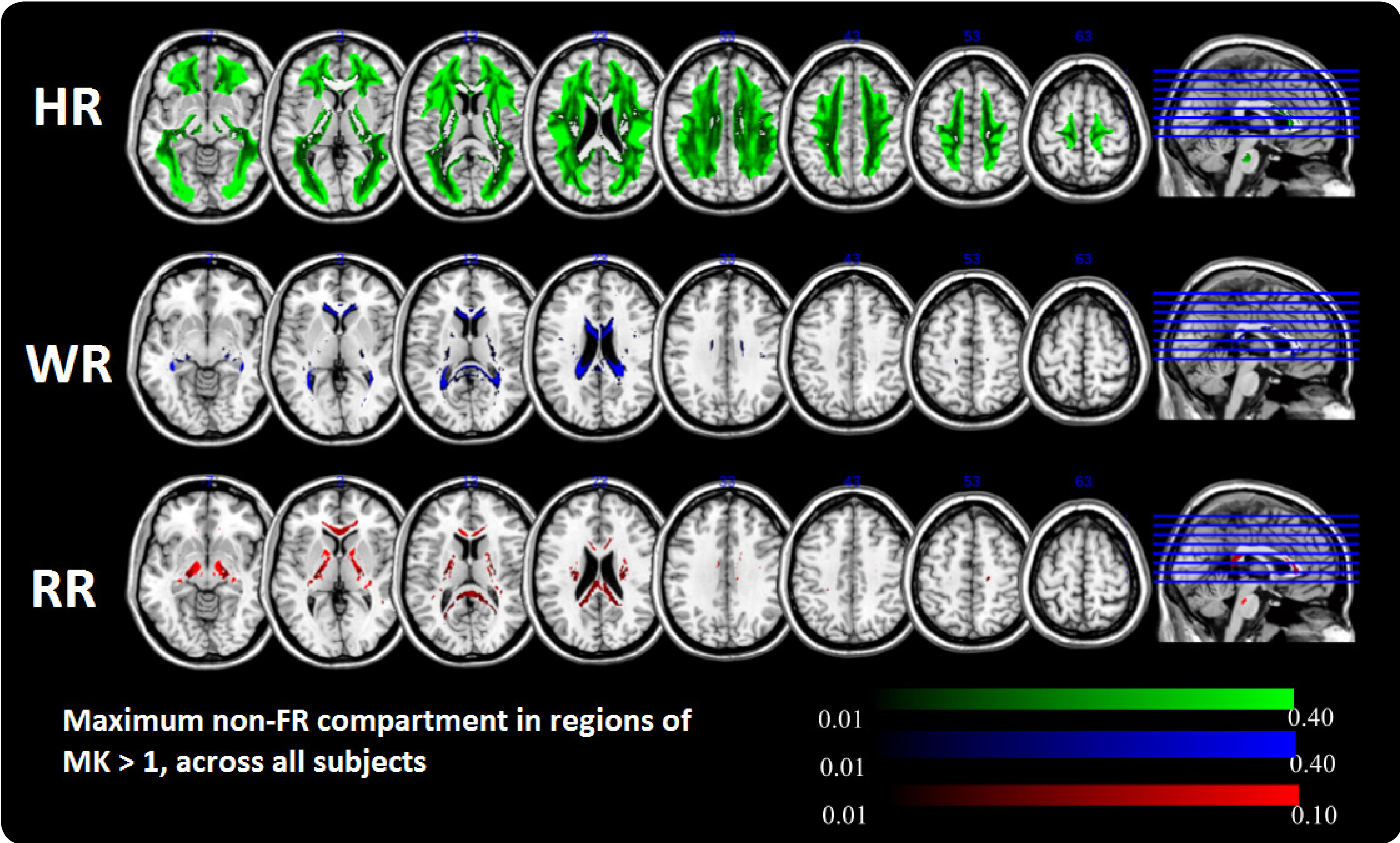


Figure 1: The maximum non-FR compartment assignment by DBSI across individuals, in regions where MK > 1.

CONCLUSIONS

We found that MK was positively associated with FR, and negatively associated with HR. These relationships were mainly driven by the RK component of MK. AK was found to be specifically and exclusively related to RR. None of the kurtosis metrics correlated strongly with the WR in areas of White Matter. The intersubject variability in the DKI-DBSI relationships was minimal, indicating that these associations are generalizable in healthy young adults. The non-FR DBSI component in regions of high MK seems to be sensitive to tissue complexity and partial volume effect.

These results can serve as a guide when comparing across DBSI and DKI studies, and for determining whether a DBSI study is concordant or discordant with a DKI study in the same population or condition. A more detailed description of this work is available in Wang et al, 2017.

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METHODS

Sample
We imaged 12 controls who are all young and healthy graduate medical students at Shanghai JiaoTong University (mean age=28.08, SD=2.54; 8 females).

Imaging
A total of 150 diffusion weighted images were collected across five different shells (30 bvectors each) with bvalues: 500, 1000, 1500, 2000 and 2500 mm/sec, along with a single unweighted b0 volume. For DKI, data were motion-corrected using FSL’s ‘eddy’ [Andersson 2016], and then smoothed with a 4mm FWHM Gaussian kernel and fit to the diffusion kurtosis tensor model using dipy v0.10 [Garyfallidis 2014]. The DBSI model was fit using in-house software.

Analysis
We compared diffusion parameters in a white matter mask defined by nonlinear SyN registration to the FMRIB template and using a 0.50 white matter probability threshold. We quantified correlation between parameters using Spearman rho, as implemented in R [R Core Development Team 2008]. WR,FR,HR and RR were extracted in regions of high kurtosis (MK >1) to examine the specificity of compartment assignment by DBSI.

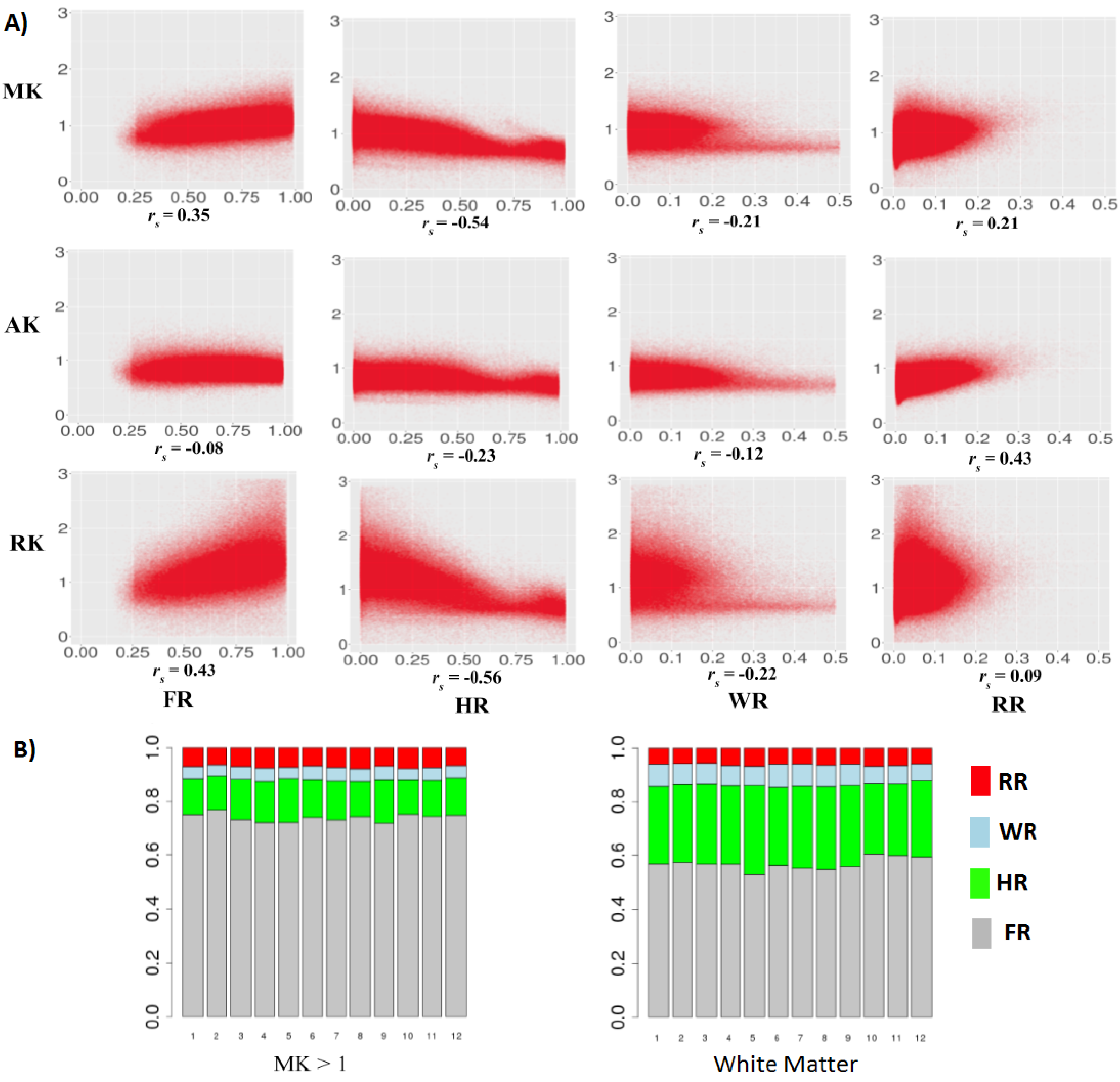


Figure 2: A) Scatterplots of DKI and DBSI parameters within white matter across all subjects, and their associated correlation coefficients. B) Compartment assignment by DBSI across individuals where MK > 1.